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Three Essays on Corporate Bonds Yield Spreads, Credit Ratings and Liquidity

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THREE ESSAYS ON CORPORATE BONDS YIELD SPREADS, CREDIT RATINGS AND LIQUIDITY

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ABSTRACT

The objective of this research is to study the relationship between various aspects of corporate bonds liquidity , transaction costs and trading activity, and their perceived credit quality as measured by credit ratings. For debt securities, Credit quality and liquidity are perhaps the most important factors that affect the investors' decisions whether to trade or hold these assets on their portfolio, as several theoretical and empirical studies identify these factors as key components of bonds yield spreads. However, the interaction and relationship between these two characteristics is not sufficiently addressed in the literature. From the investors' perspective, it is beneficial to know whether they face a tradeoff between credit quality and liquidity or if both desirable features move in the same direction. We use more than twelve years of Enhanced TRACE data from 2002 to 2014 to analyze the liquidity of corporate bonds both cross-sectionally across credit ratings and intertemporally around credit rating changes.

The first manuscript studies the relationship between corporate bonds' credit risk and their market liquidity, and the dynamics of this relationship over the period from 2002 to 2014. Unlike the implication of theoretical models, our findings do not empirically support a monotonically positive relation between credit risk and transaction costs. Instead, we find an inverted U-shaped relationship where bonds with ratings near the Investment grade/ High yield boundary have the largest transaction costs (lowest liquidity) after controlling for other relevant factors. One explanation for this finding is that bond dealers behave more as brokers in speculative grade bonds and are reluctant to enter overnight positions in these risky securities, unless they find

the other side of the trade. This kind of dealers behavior potentially reduces the transaction costs of lower rated bond, as captured by bid-ask spreads, to only reflect the cost of searching for counterparty rather than inventory or adverse selection risks, and may be even more pronounced during distressed market conditions due to more capital constrains and less funding liquidity. Consistent with this explanation, using a Markov Switching time series model, we find that while bid-ask spreads significantly increase for investment grade bonds during the crisis, they stay invariant for junk bonds.

The second essay expands this investigation to examine the impact of rating changes on corporate bonds' liquidity around the rating change announcements using an event study methodology. Many institutional investors such as insurance companies or pension funds are prohibited by regulations from investing substantial portion of their portfolios in risky bonds. Hence, the rating changes that move the bonds out of the investment grade category can elicit selling pressure or even fire sale of the fallen angels. Beyond just the investment grade issue, prudential regulators also have scoring algorithms that require more capital to be held as ratings fall. Our findings suggest an abnormal decrease in liquidity following the rating downgrades with more severe impact for downgrades that move the bond from investment grade to high yield category. Consistent with the prior findings, investment grade bonds liquidity is more sensitive to rating downgrades and for bonds that are already risky, further downgrades doesn't seem to affect their liquidity and transaction costs significantly. We also find that bond and issuer characteristics like issue size and industry group affect the liquidity conditions around rating events.

The third essay reviews the theoretical as well as empirical literature on the impact of liquidity on corporate bonds prices and yield spreads.

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PREFACE

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Credit Ratings and Corporate Bond Liquidity

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ABSTRACT

This paper studies the relationship between corporate bonds' credit risk and their market liquidity, as well as the dynamics of this relationship from 2002 to 2014. Unlike the implication of theoretical models, our findings do not empirically support a monotonically positive relation between credit risk and transaction costs. Instead, we find an inverted U-shaped relationship where bonds with ratings near the investment grade/ high yield boundary have the largest transaction costs (lowest liquidity) after controlling for other relevant factors. One explanation is that bond dealers behave more as brokers in speculative grade bonds and are reluctant to enter overnight positions in these risky securities, unless they find the other side of the trade, as suggested in Goldstein and Hotchkiss (2017). This type of dealer behavior potentially reduces the transaction costs of lower rated bond, as captured by bid-ask spreads, to only reflect the cost of searching for counterparty rather than inventory or adverse selection risks, and may be even more pronounced during distressed market conditions due to more capital constrains and less funding liquidity. Consistent with this explanation, using a Markov Switching time series model, we find that where bid-ask spreads significantly increase for investment grade bonds during the crisis, they stay invariant for junk bonds.

1. Introduction

This paper studies the relationship between corporate bonds' trading costs and perceived credit quality as measured by their credit ratings. The nationally recognized statistical rating organizations (NRSRO's) such as Moody's and Standard and Poor's have been rating corporate bonds for over a century, and a broad array of contractual and regulatory requirements are tightly connected to the ratings they provide. Although at times the incentives and ability of rating agencies to provide accurate and timely information have been called into question, credit ratings are widely used by investors and regulators alike as proxy for credit risk. In addition, different regulations use credit ratings to restrict investment or allocate risk: institutional investors such as insurance companies and pension funds are prohibited from investing significant proportion of their portfolio in high yield bonds, and risk based capital requirements for banks and other financial intermediaries are also determined based on credit ratings. As a result, the potential pool of investors, their trading frequency and strategy may vary across credit ratings. This variation may affect dealers' trading behavior, and ultimately liquidity and transaction costs for corporate bonds across different rating categories.

Traditional market microstructure models generally imply wider bid-ask spreads for lower rated bonds, conditional on certain assumptions. For example, inventory models relate bid-ask spreads to dealers' inventory risk which increases with the degree of asset price movements as well as the length of time the asset is kept in inventory (Stoll, 1978; Ho 1981; Ho and Stoll, 1983; Grossman and Miller, 1988; Brunnermeier and Pedersen, 2008). Since lower rated bonds may experience higher price volatility and it may take longer time for the dealers to find a trading counterparty for risky bonds, this group of models suggest larger trading costs for low rated bonds.

Based on asymmetric information models such as Glosten and Milgrom (1985) and Kyle (1985), bid-ask spreads are affected by the risk of trading against informed traders and increases with the degree of information asymmetry in the market and asset value uncertainty. Given the higher level of uncertainty regarding the future cash flows generated by riskier assets, dealers may charge wider spreads that compensate them for the risk. Moreover, although a significant proportion of investors in both investment grade and high yield bonds consist of large and sophisticated financial institutions, the type of institutions and their incentive to trade may vary for investment grade versus high yield bonds. For example insurance companies and pension funds are mainly buy-and-hold investors in investment grade bonds, whereas hedge funds and high yield mutual funds that trade lower rated bonds may follow more speculative strategies.

Recently the structural credit risk models with endogenous liquidity proposed by He and Milbradt (2014) and Chen, Cui, He and Milbradt (2015) also predict a positive relationship between corporate bonds credit risk and bid-ask spreads. [3]

[3] He and Milbradt (2014) and Chen, Cui, He and Milbradt (2015) adapt the search and bargaining framework of Duffy, Gârleanu, and Pedersen (2005) to model the secondary market for corporate bonds. Two types of investors exist in their model: High type and Low type. High type investors are the ones that incur no cost for holding the asset. Low type investors are the ones affected by an exogenous liquidity shock and incur holding cost, so they search for a dealer to get rid of the bond. Chen, Cui, He and Milbradt (2015) model this holding cost in light of collateralized borrowing and assume that the bond is part of a large portfolio including leverage and can be used as collateral for these loans. Borrowing against the bond involves a haircut. A decline in a bonds credit quality pushes down its market price and increases the haircut. This in turn drives down the low type investor valuation of the bond and widens the valuation wedge between high type and low type investors. Since the bid-ask

Empirically, the evidence is mixed. Hong and Warga (2000), Chakravarty and Sarkar (2003), Harris and Piwowar (2006), and Edwards, Harris and Piwowar (2007) find that lower rated bonds have larger transaction costs. On the other hand, Schultz (2001), Bao, Pan and Wang (2011), and Goldstein and Hotchkiss (2017) find no significant relation between ratings and liquidity. In some of the previous studies, high yield bonds are either eliminated from the sample or are grouped in one or two big rating classes. Moreover, many of these studies predate the recent financial crisis which may have affected the relation between credit ratings and liquidity and the possible time variation in this relationship is often overlooked.[4]

This study contributes to the literature by examining the dynamics and dimensions of bond market liquidity across the entire spectrum of credit ratings using more than twelve years of TRACE data from 2002 to 2014 and seven different liquidity measures: a price impact measure, three spread measures, and three trading activity measures.[5] As this period includes the financial crisis, this study also examines the effect of market distress and how liquidity varied across different rating categories, and whether the post-crisis regulations aiming to limit risk taking by

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spread in their model is a function of investors bargaining power and the valuation wedge between low type and high type investors, the above procedure results in a rise in the bid-ask spread.

[4]The corporate bond market has changed dramatically since the recent financial crisis. Some new trends include huge amount of bond issuance, investors search for higher yield due to the nearly zero interest rates, great reduction in bond dealer's net inventory positions in corporate bond, changes in their risk management practices and improvements in electronic trading venues. These new trends have affected the trading behavior of both investors and market makers and it is reasonable to assume that they may affect the liquidity and transactions cost across different credit ratings.

[5]Since Hamilton and Cantor (2004) note, the frequency of default increases non-linearly across ratings, credit rating is not treated as a continuous variable in this study. Hamilton and Cantor (2004) document three year default rates of 0.0%, 0.0%, 0.4%, 1.5%, 4.4%, 17.7% and 31% for Aaa, Aa, A, Baa, Ba, B and Caa bonds respectively.

banking institutions, mainly the Volker Rule of Dodd-Frank Act, has adversely affected market liquidity of investment grade and high yield bonds.

The results show that the relation between credit rating and liquidity depends in part on how liquidity is defined. Not only are there differences by liquidity measure, but there are also notable non-linearities; for example, the Amihud price impact measure suggests that market resilience decreases for lower rated bonds. However, in contrast to the common wisdom and the implications of theoretical models, we don't find evidence of a monotonic increase in bid-ask spreads as we move to lower rated bonds. Instead, bid-ask spread measures suggest more of a step function, where spreads become notably higher just at the investment grade/high yield (BBB/BB) cutoff, and then decline. Trading activity across rating classes also show that high yield bonds are on average more actively traded in terms of both number of trades and volume after controlling for other relevant factors. There is also lower percentage of zero trading days for lower rated bonds. Piecewise panel regressions suggest similar results, implying a different relation between liquidity and credit quality within investment grade versus high yield bonds.

To examine the dynamic liquidity behavior of investment grade vs. high yield categories, the monthly aggregate liquidity and trading activity time series is modeled as Markov switching AR(k) processes. Our findings suggest that during the normal periods, the aggregate transaction cost for riskier bonds is higher compared to low risk bonds, but there is an abrupt regime change during the financial crisis period: spreads increase dramatically for investment grade bonds, but remain relatively constant for high-yield bonds. While the spreads for riskier bonds are quite low in dollar terms, as a percentage of price, these spreads are higher than the normal periods due to the sharp decline in junk bond prices during this period. Post-crisis and during the recent period of regulatory changes, the results suggest an increase in the aggregate market liquidity as measured by price impact and bid-ask spreads and higher aggregate trading activity. The absolute bid-ask spreads for high yield bonds converge to a level above the spreads for investment grade bonds during post-crisis and regulatory periods.

To study further the time variation in the relationship between bonds liquidity and credit quality, we rerun the panel regressions with rating dummies and bond and issuer controls separately on three sub-periods: *Pre-crisis* which we define as the period from Jul. 2002 to Nov. 2007, *crisis* which is the period from Dec. 2007 to June 2009 and *post-crisis* which we define as the period from July 2009 to Sep. 2014. Results show that during the pre-crisis period, although non-monotonically, trading costs increase for lower rated bonds, which is consistent with the findings of some previous studies that used the pre-crisis bond market data such as Hong and Warga (2000), Chacravarty and Sarkar (2003), Harris and Piwowar (2006), and Edwards, Harris and Piwowar (2007). However, the panel regressions show that consistent with the results from Markov-switching model time series analysis, after and particularly during the crisis, regression coefficients become larger as we move to lower rating dummies within the investment grade range, while they become insignificant or negative as we move to lower rated bonds within the high yield category.

A possible explanation for these findings is the heterogeneous trading behavior and market making activity of bond dealers for investment grade versus high yield bonds. We argue that dealers may be less willing to commit capital to hold riskier bonds in inventory and behave more as brokers in these types of securities, particularly during periods of market distress when they face more capital constraints. As a result the observed bid-ask spreads may be more close to brokerage commission fees and reflect dealers search costs rather than their inventory risk.

This view is supported by a number of previous studies. An earlier evidence of this kind of behavior is documented by Bessembinder and Maxwell (2008) during the period following the initiation of TRACE as a side effect of increased transparency. According to Bessembinder and Maxwell (2008), "(p)ost-TRACE, bond dealers no longer hold large inventories of bonds for some of the most active issues; for less-active bonds they now serve only as brokers". Goldstein, Hotchkiss, and Sirri (2007) find that dealers perform a matching brokerage function in illiquid bonds. Feldhütter (2012), models OTC bond markets based on Duffie, Gârleanu, and Pedersen (2005) framework and assumes segmented markets by trading size during liquidity shocks. He argues that during liquidity shocks risk limits often prohibit market makers from taking the bond on the book and splitting large trades. In this situation it is often the case that the sales person of the bank directly searches for a buyer and "typically, the bid-ask fee is collected by the sales person not the market maker". More recently Goldstein and Hotchkiss (2017) show that dealers are most likely to quickly offset trades rather than holding bonds in inventory overnight or longer for the least actively traded or riskier bonds.

This line of reasoning implies that the notion of bid-ask spreads as the price of "immediacy" services provided by dealers may not hold for riskier or less actively traded bonds, particularly during liquidity shocks. Therefore, caution should be taken interpreting narrower bid-ask spreads on riskier bonds as an indication of better liquidity condition. Instead, the risk of price movement may be shifted to investors, particularly during liquidity shocks when they need to wait longer for the opposite side of the trade to arrive.

The rest of the paper is organized as follows: Section 2 describes the data and summary statistics, Section 3 describes the liquidity measures used in this study and their summary statistics, Section 4 analyzes the illiquidity across credit ratings, Section 5 analyzes the time series behavior of (il)liquidity and trading activity measures, Section 6 discuss the robustness tests and Section 7 concludes the paper.

2. Data and summary statistics

Two main sources of data for this study are Enhanced Historic TRACE corporate bond data, and Mergent Fixed Income Securities Database (FISD). Since July 2002, all corporate bond transactions in the secondary market have been disseminated through the TRACE system (Trade Reporting and Compliance Engine). The enhanced data improves the standard TRACE data in three ways: First, it contains reports of all transactions since July 2002 including transactions in formerly non-disseminated bonds (except 144A bonds). Second, it contains uncapped transaction volumes and historical buy-sell side information as the most significant improvements over the standard data. Finally, the enhanced data contains some more specialized information such as information on reporting date and time which allows for a better error filtering algorithm. The enhanced information comes at a cost of an 18 month lag in availability of the data (Dick-Nielsen, 2014). Although, the newest standard TRACE data includes all non-144A transactions and buy/sell side indicators, it is still missing the uncapped volumes when compared to the enhanced data.

This study covers the period from the initiation of TRACE in July 2002 to September 2014. The Enhanced TRACE data for the observation period includes 141,997,423 transactions for 112,879 bonds. Panel A of Table 1 shows the result of applying Dick-Nielsen (2014) filtering procedure which includes the following steps: First, deleting same-day corrections and cancelations. Same-day refers to corrections and cancelations reported within the same reporting date (not transaction date). Applying this step deletes 4.4% of transactions and 0.35% of bonds from the original sample. Second, removing reversals and the matching original transaction report. Around 1.6% of transactions and 0.09% of bonds are eliminated after this step. Third, removing agency transactions where the principal transaction has the same price as the agency transaction which is a kind of double counting. This step deletes 5% of transactions and 4.21% of bonds. Fourth, removing one of the reports in each interdealer transaction pair and classify the retained report as an interdealer transaction. We also exclude special transactions such as trades which are not secondary market, trades under special circumstances, commissioned transactions, odd number of days to settlement, automatic give up trades, non cash sales. Applying this step eliminates around 28% of transactions and around 18% of bonds. In general, as a result of implementing the above procedure, 55,455,418 transactions and 25,658 bonds are deleted from the original sample.

In order to make sure that the results are not affected by possible outliers, we modify the Edwards, Harris and Piwowar (2007) approach and apply 20% median filter which eliminates a bond price if it deviates from daily median price by more than 20%, as well as a 50% return reversal filter which eliminates a bond price if it is preceded and followed by a price increase or drop of more than 50%. The final Enhanced TRACE sample consists of 86,450,187 observations for 87,159 bonds.

Bond characteristics such as issue date, issue size, delivery date, coupon rate, maturity, issuer name, industry and ratings from the main three credit rating agencies, i.e. Moody's, Standard & Poor's, and Fitch are obtained from Mergent FISD. [6] We include only the bonds that remain in the data at least for one year. Furthermore, following the literature on corporate bond market, we exclude issues that are denominated in a currency other than US dollar or have a foreign issuer, variable rate and zero coupon bonds, bonds that have credit enhancement, convertibles, asset-backed, callable, putable, exchangeable, fungible, preferred, tendered, and bonds that are part of a unit deal. We include bonds issued by corporations in three industry group including Industrial, Finance and Utility. Panel B of Table 1 shows the results of applying these filters on FISD data. The final FISD sample includes 6,549 bonds issued by 1,271 companies. After merging cleaned Enhanced TRACE and FISD, we obtain 7,988,836 transactions on 3,118 trading days for 4,065 bonds issued by 1,187 firms.

The corporate bond market is characterized by illiquidity. More than 76% of the sample bonds are not traded on at least one month of their existence in the sample. However, the liquidity measures can only be calculated for bonds with sufficient

[6] Moody's, Standard and Poor's, and Fitch nationally recognized statistical rating organizations, or rating agencies that are regulated by the U. S. Securities and Exchange Commission; see Senate Bill 3850 (109th Congress), The Credit Rating Agency Reform Act of 2006, https://www.govtrack.us/congress/bills/109/s3850/text.

number of transactions. Hence, we only keep the bonds that are traded on at least 4 distinct days and are traded at least two times during each trading day in the sample. After applying these filters, the final sample includes 7,640,266 observations for 3909 bonds issued by 1,173 firms.

Table 2 shows the summary statistics of the final sample by year and rating groups. In order to compare the characteristics of the final sample with that of the original Enhanced TRACE-FISD merged data (before imposing FISD filters), we also report the summary statistics for the original data in Panel B of Table 2. As we can see from the second column, the number of bonds existing in the final sample gradually decreases throughout the sample period. This is mainly due to the notable increase in the number of variable rate, non US dollar denominated or foreign issuer bonds from 2002 to 2014. The percentage of variable rate and zero coupon bonds in the Enhanced TRACE-FISD merged sample increased from around 9% in 2002 to around 34% in 2014. Also, the percentage of non US dollar denominated and foreign issuer bonds has increased from around 6% in 2002 to around 20% in 2014. On average about 81% of bonds that are alive in the sample during each year have at least one trade during that year. Mean and median issue size in the final sample is \$351 million and \$100 million respectively. The average issue size has increased gradually by years in both samples particularly after the financial crisis due to the low interest rate environment which has made debt financing for companies substantially cheaper. However column 3 and 4 of Table 2 show that generally the final sample consists of bonds with larger issue size. The representative bond in the original and final sample is investment grade, with a median rating in final sample close to 6 which translates to Moody's A2 and Standard and Poor's A. On average, bonds existing in the final sample throughout the entire sample period have higher ratings compared to the original sample. The average time to maturity is 6.6 years and the average age is 8.6 years. The original sample on average consists of bonds with longer time to maturity and shorter age in most of the years. Over time, we see a gradual increase in mean and median age in our final sample. As we would expect the lowest average prices during the study period belongs to 2008 and 2009 for both samples. We can also observe that after 2012 the average bond price has increased substantially compared to previous periods. Bonds in the final sample generally have higher prices which is consistent with their higher quality. Finally, the average number of bonds issued by the same issuer is higher in the final sample compared to the original sample.

In summary the comparison between the original and final sample shows that the bonds analyzed in this study on average have larger issue size, higher rating and higher price and are issued by issuers with larger number of bonds outstanding compared to the original Enhanced TRACE-FISD sample.

Panel C of Table 2 shows the number of bonds and summary statistics of the final sample by rating group. On average, higher rated bonds tend to have larger issue size, lower coupon rate, shorter age, shorter time to maturity and higher price. Also higher rated bonds are generally issued by firms with larger number of issues outstanding.

3. Liquidity measures

In this study, we examine different aspects of liquidity by using several measures calculated on a monthly basis. The first measure, Amihud is as price impact measure, Three bid -ask spread proxies: A round-trip cost measure proposed by the authors

(RTC), Hong and Warga (HW)(Hong and Warga (2000) ;Chakravarty and Sarkar (2003)), Riskless principal trades markup (RPT) recently proposed by Harris (2015), and three trading activity measures including trading volume, number of trades and percentage of zero trading days in a month (Zero) (Lesmond, Ogden and Trzcinka(1999), Dick-Nielsen, Feldhütter and Lando (2012)). All these proxies, except volume and number of trades are in fact illiquidity measures.

A substantial proportion of the variation in percentage bid-ask spreads across ratings may be due to the price differences between high rated versus low rated bonds, which incorporates the credit risk associated with each rating. As a result, as we move from high rated to low rated bonds the average of bid and ask prices declines and naturally pushes up the relative measures of bid-ask spreads. To eliminate this effect and to focus on the dollar value of transaction costs, we calculate the bid-ask spread measures in the absolute form.

Having buy/sell side indicators in the Enhanced Trace sample allows us to compute a new roundtrip-cost measure (RTC) in the spirit of Feldhütter (2012)'s IRC, which was originally calculated without having buy/sell side information. As Feldhütter (2012) pointed out, calculating imputed roundtrip cost without having the order sign, results in underestimating the transactions costs. We incorporate order sign information in our proposed measure to remove this bias. We also include Riskless Principal Trade's markup (RPT) measure recently proposed by Harris (2015) in our analysis. The detailed explanation of the procedure for calculating liquidity measures and a thorough analysis of the behavior of the latter new measures are included in the Appendix.

Panel A of Table 3 shows the summary statistics for liquidity measures. The mean percentage of zero-trading days is 74% and the median is 90%, which demonstrate a high degree of illiquidity in our sample of corporate bonds. The median Amihud measure is 0.32 implying that a trade of $300,000 in an average bond, for example, moves price by roughly 9.6%, smaller than the 10.2% found by Han and Zhou (2008). In contrast the Amihud measure computed in Dick-Nielsen, Feldhütter and Lando (2012) imply that a trade of $300,000 in an average bond moves the price by roughly 0.13% which is much lower compared to Han and Zhou (2008) and our results. This notable difference is due to the fact that Dick-Nielsen, Feldhütter and Lando (2012) only focus on institutional size trades in their study. The average roundtrip cost (RTC) for our sample is 65 cents which is relatively larger compared to the average IRC of 59 cents found by Feldhütter (2012). However, it's worth mentioning that nearly 79% of transactions in our sample consist of retail size trades below $100,000 and around 40% of transactions are between $10,000 and $50,000 (See Table 1 in the Appendix). As documented in several papers, transaction costs are higher for smaller trades (e.g. Schultz (2001), Chacravarty and Sarkar (2003), and Edwards, Harris and Piwowar (2007)). Moreover, as mentioned earlier, the IRC measure calculated in Feldhütter (2012) tend to underestimate the transaction costs. The RTC is only 1 cent for the 5% most liquid bonds. Other bid-ask proxies demonstrate comparable mean and median values. The mean and median RPT markup is 67 cents and 52 cents respectively. Generally, consistent with the findings in, Bessembinder, Maxwell, and Venkaraman (2006), Goldstein, Hotchkiss and Sirri

(2007), Edwards, Harris and Piwowar (2007) and Feldhütter (2012), we find modest average transaction costs for our sample of corporate bonds.

Panel B of Table 3 shows the correlation among liquidity measures and their significance. There is 54% percent correlation between Amihud market depth measure and bid-ask spread as proxied by roundtrip cost (RTC). There is 32% percent correlation between Amihud and riskless principal trades (RTC) markup. Amihud is positively and significantly correlated with zero-trading days meaning that as the number of days in a month with at least one trade decrease, the price impact of trades will increase. This result is in contrast with Dick-Nielsen, Feldhutter and Lando (2012), as they found a negative correlation between quarterly Amihud measure and zero-trading days measure. There is nearly zero correlation between riskless principal trades' markup (RPT) and monthly volume as well as zero-trading days. Finally, we can observe negative and significant correlations among trading volume and Amihud, RTC and HW measures.

Panel C of Table 3 shows the mean liquidity measures by rating group. We can see that on average, the Amihud measure is higher for lower rated bonds. The average bid-ask measures increase for lower rated bonds and have the highest value for BB/Ba-B rating group and then decline for ratings equal or below CCC/Caa. The average volume is highest for AAA-AA/Aa bonds and for ratings equal or below CCC/Caa and the monthly number of trades has the highest value for AAA-AA/Aa bonds.

4. Regression analysis

4.1 Panel regressions on entire sample

The goal of this study is to investigate how various aspects of liquidity vary across credit ratings. Previous studies such as Hong and Warga (2000), Chacravarty and Sarkar (2003), Harris and Piwowar (2006) and Edwards, Harris and Piwowar (2007)[7] find that lower credit ratings are associated with higher transaction costs. Other studies do not find a clear relation between credit ratings and transaction costs (or measures of (il)liquidity. For example, Schultz (2001), find no evidence of larger trading costs for lower rated bonds for a sample of daily bond transaction records of insurance companies. Bao, Pan and Wang (2011) find no significant relation between credit ratings and liquidity in their analysis of the relationship between bond characteristics and their proposed illiquidity measure on a sample of investment grade bonds. Also, holding trading or volume constant, Goldstein and Hotchkiss (2017) find no significant relation between ratings and liquidity.[8]

The current study contributes to the existing literature in several ways. First, we investigate the non-linearities in the relationship between corporate bond credit ratings and liquidity which is usually overlooked in previous research. Next, unlike previous studies which mostly focus on the investment grade ratings, the current analysis covers

[7]For example, Edwards, Harris and Piwowar (2007) estimate the effective half spread for trade size of 20 bonds ($20,000) to be 3.4 for BBB bonds, 17.9 for B or BB bonds and 43.8 for bond with C rating and below.

[8]Very few theoretical papers explicitly address this relationship. He and Xiong (2012), He and Milbradt (2014) and Chen, Cui, He and Milbradt (2015) models based on the structural credit risk models of Leland (1994) and Leland and Toft (1996) and search model of Duffie, Gârleanu, and Pedersen (2005) are consistent with the empirical findings of Bao, Pan and Wang (2011), Dick-Nielsen, Feldhütter and Lando (2012) and Friewald, Jankowitsch and Subrahmanyam (2012)that corporate bonds with higher credit ratings have lower transaction costs and that corporate bonds are less liquid during economic downturns, especially for riskier bonds.

the full spectrum of credit ratings including bonds close to default.[9] Finally, we study different aspects of liquidity using a variety of liquidity proxies which helps us better understand the possible heterogeneous relation between credit ratings and various liquidity dimensions.

We start by conducting a multivariate, level analysis to test whether the liquidity for each letter rating class is significantly different from a benchmark and how the mean liquidity varies across rating classes, after controlling for other relevant factors. We run seven panel regressions in the following form:[10]

$$ILLIQ_{it} = \alpha 1 + \alpha 2 Aa_{it} + \alpha 3 A_{it} + \alpha 4 Baa_{it} + \alpha 5 Ba_{it} + \alpha 6 B_{it} + \alpha 7 Caa_{it}$$
$$+ \alpha 8 Ca / C_{it} + \mathbf{Controls}_{it} + \delta_k + \varepsilon_{it} \quad (1)$$

Where $ILLIQ_{it}$, the dependent variable, is a different liquidity proxy in each regression. Aa_{it} , …, Ca/C_{it}, are dummy variables taking the value of 1 if the bond's rating is in Aa,…,Ca/C rating class and 0 otherwise. Aaa rating class is chosen as the benchmark group. The $\boldsymbol{Controls}_{it}$vector includes the bond level and firm level characteristics that are commonly used in the literature as determinants of corporate bond liquidity: maturity, coupon, age, issue size, coupon frequency, number of bonds issued by the same firm, issuer's industry, average monthly trade size and monthly percentage of institutional size trades in a bond. We control for the market-wide variations in liquidity over time by including the year fixed effect in the model, δ_k,

[9]Jankowitsch et al. (2014) document temporary high trading activity and price pressure on the default event day itself exclusively.

[10] . The dependent variables in these regressions have limited range, for example monthly volume is always a positive number and bid-ask spread measures are left censored. We have tested the sensitivity of our models to the limited range of variables, using Tobit regression method in Appendix B. Generally the results are not affected after controlling for left-censored dependent variables in our regressions.

where k is the year indicator (k=1 for 2002,…,k=13 for 2014). By estimating the above model, we assume that each rating class has a different liquidity level (intercept), controlling for other factors and test how these levels vary across rating classes and whether they are significantly different from the liquidity level of the benchmark group (Aaa/AAA). We also assume that the effect of control variables on liquidity is not significantly different across rating classes. $\alpha_1, \ldots, \alpha_8$ represent the difference between the expected iliquidity, $E(ILLIQ_{it}|\boldsymbol{Controls}_{it}, \delta_k)$, of each letter rating class with the expected iliquidity of the benchmark group. Each issuer in our sample may have multiple bonds outstanding with highly correlated characteristics. Hence, we correct the standard errors by clustering observations at the issuer level and also control for heteroscedasticity using White-Huber robust standard errors.[11]

Table 4 shows the results for the above regression analysis. Columns 2 to 8 of Table 4 show the regression coefficients and their significance levels for each liquidity and trading activity measure. To better see how the intercepts ($\alpha_1, \ldots, \alpha_8$) vary by credit ratings, Figure 1 shows the (il)liquidity intercept of each rating class for different (il)liquidity proxies and their 95% confidence intervals. Using monthly Amihud measure as dependent variable, we observe that the illiquidity levels for investment grade rating classes are not statistically different from that of Aaa rating. However, the coefficient for Aa is negative and significant at 0.1 level implying that controlling for other relevant factors, Aa rated bonds have slightly lower Amihud measure. The coefficients for rating classes within the speculative grade range are positive and highly significant indicating that trading speculative grade bonds is

[11]To save space the t-statistics are not reported and are available upon request.

associated with significantly higher price impact. As Figure 1 shows, the mean Amihud is particularly high for bonds close to default (Ca/CC/C rated bonds). For example the 0.51 value for the coefficient of Ca/CC rated bonds tells us that holding other factors constant, a trade of $300,000 in a Ca/CC rated bond moves the price by 15.3% more than a trade of the same size in Aaa/AAA bonds.

The results for the bid-ask spreads as measured by three proxies: *RTC*, *HW* and *RPT* are quite different from what observed for the Amihud measure. The graph of α coefficients in Figure 1 show a nearly inverted U-shaped relationship between the absolute bid-ask spreads and credit ratings using all three proxies. As we can see in Panel B of Figure 1, the maximum value for expected bid-ask spread belongs to Ba/BB rated bonds which is the rating class right below the investment grade boundary. The Expected spread for Aa/AA rated bonds (as proxied by *RTC* and *HW*) is significantly lower than that of Aaa/AAA bonds. The expected bid-ask spread increases as we move from Aa/AA rating to Investment grade boundary and then starts to decline for speculative grade bonds.

Analyzing the relationship between credit ratings and monthly trading activity variables also reveals interesting results. As we can see from both columns 6 to 8 of Table 4 and Figure 1, after controlling for bond and issuer level characteristics that affect trading activity, both monthly number of trades and monthly volume increase when we move from investment grade to speculative grade ratings. These results are consistent with the notion that the majority of the investors in investment grade bonds are large institutions with buy-and-hold strategy and after the investment grade bonds are placed in the portfolios of these institutional investors they are rarely traded. The average percentage of monthly zero trading days also declines significantly as we move from investment grade to non-investment grade category. These results are consistent with a recent evidence provided by Mizrach (2015). Dividing the corporate bond market to two segments based on trading activity (1000 most active issues and the rest), he finds that the percentage of investment grade bonds in the active trading group is less than their percentage in the less active trading group for their entire sample period from 2003 to 2015. In particular, he finds that on average 35% of the bonds in the less active category have A ratings.

Overall, the results from Table 4 and Figure 1 show that various dimensions of liquidity vary differently and non-linearly across ratings. The Amihud price impact measure increases as we move towards the lower rated bonds, whereas the transaction costs in the form of bid-ask spread seem to be highest for bonds with ratings close to investment grade boundary and declines for lower rated high yield bonds. Specifically, the results from Table 4 and Figure 1 appear to suggest two distinct liquidity regimes among Investment grade and high yield bonds. To further explore the non-linear nature of the relationship between ratings and liquidity and to quantify the liquidity differences among the three regimes, we examine a piecewise regression model in the following from:

$$ILLIQ_{it} = \alpha_1 + \alpha_2 Junk_{it} + \beta_1 Rating_{it} + \beta_2 Junk_{it} \times (Rating_{it} - 11) + \mathbf{Controls}_{it} + \delta_k + \varepsilon_{it} \qquad (2)$$

Where $ILLIQ_{it}$ is one of the seven liquidity measures in each regression, $Junk_{it}$ is a dummy variable equal to 1 if the bond has rating below Baa3 and 0 otherwise, and

$Rating_{it}$ is a discrete variable taking values 1 to 21 for bonds with Aaa/AAA,…,C ratings respectively. $\mathbf{Controls}_{it}$ vector includes the control variables used in the previous regression. We also control for time variation in liquidity using years fixed effect (δ_k).

Estimating the piecewise model as described above results in two distinct regression lines for Investment grade and high yield bonds. We test whether these regressions lines are statistically different:

$$ILLIQ_{it} = \begin{cases} \alpha_1 + \beta_1 Rating_{it} + \mathbf{Controls}_{it} + \delta_k + \varepsilon_{it} & if\ Rating_{it} < 11 \\ (\alpha_1 + \alpha_2 - 11\beta_2) + (\beta_1 + \beta_2) Rating_{it} + \mathbf{Controls}_{it} + \delta_k + \varepsilon_{it} & if\ Rating_{it} \geq 11 \end{cases} \quad (3)$$

Table 5 reports the results of piecewise regressions for each liquidity measure. To save space we don't report the coefficients and t-statistics of control variables, as they are roughly similar to the values observed in Table 4. Column 2 shows the results for Amihud measure. The significant and positive coefficient for $Rating_{it}$ shows that the price impact is larger for lower rated bonds within the investment grade category. The positive and highly significant β_2 shows that within the high yield range, Amihud increases more as we move to lower rated bonds.

Figure 2 helps us better understand the results from Table 5. Panel A of Figure 2 illustrates the results for Amihud measure. The piecewise model allows us to quantify the magnitude of breaks among three regression lines for each measure. Columns 3 to 8 of Table 5 and Panel 2 of Figure 2 show the results for bid- ask spread and trading activity measures. We can see that the bid-ask spreads increase significantly as we move to lower rated bonds within the investment grade range. The regression slopes for high yield bonds is negative and significantly different from that of investment grade bonds. For trading activity measures, the results show that the monthly number of trades and volume significantly increase as we move to lower rated bonds within investment grade category, whereas the percentage of zero trading days remains quite constant across the investment grade bonds. Generally the number of trades and volume is significantly higher and the percentage zero trading days is significantly lower for high yield bonds. Generally the results of piecewise regressions are consistent with the findings from Table 4 and shed more light on the non-linear relationship between credit ratings and liquidity of corporate bonds.

4.2 Panel regression on sample sub-periods

In the previous section, we explored the relationship between various measures of liquidity and credit ratings over the entire sample period. However, our sample includes the period of recent financial crisis which is characterized by several bank failures, downgrades, severe liquidity shocks and funding constraints faced by bond traders. These events may have a significant impact on the relative liquidity and trading costs across rating classes.

To study the possible time variation in the relationship between bonds liquidity and their credit quality, in this section we rerun the panel regression analyses of equation 1 for various liquidity measures on three separate sub samples: *Pre-crisis* which we define as the period from Jul. 2002 to Nov. 2007, *crisis* which is the period from Dec. 2007 to June 2009 and *post-crisis* which we define as the period from July 2009 to Sep.2014.

The results of these regressions are reported in Table 6 and Figure 3. Since our focus is the coefficients of the rating dummies, to save space the coefficients of the control variables are not reported in Table 6. Panel A shows the results for pre-crisis period. We can observe that during the pre-crisis period, although non-monotonically, the rating dummies' coefficients are positive and significant for ratings equal and below BBB/Baa and increase as we move to lower rated bonds. These results are in line with the findings of some previous studies that used the pre-crisis bond market data such as Hong and Warga (2000), Chacravarty and Sarkar (2003), Harris and Piwowar (2006), and Edwards, Harris and Piwowar (2007) and find larger trading costs for lower rated bonds.

Panel B and C of Table 6 show the results for crisis and post-crisis periods. For regressions with Amihud measure as the dependent variable, we can see that the coefficients for ratings equal or below BBB/Baa are positive, significant, and larger compared to the pre-crisis period but are mostly negative and insignificant during the post-crisis period. For bid-ask spread measures the coefficients are negative and significant for high yield bonds particularly for ratings equal or below Caa/CCC category during the crisis and mostly negative but insignificant for post-crisis period. These results show an interesting phenomenon that during the financial crisis high yield bonds trade at lower bid-ask spread levels. To further examine the liquidity dynamics of investment grade versus high yield bonds, in the next section we conduct a time series regime switching analyses that enables us to identify the possible regime shifts in aggregate market liquidity as well as investment grade versus high yield categories.

5. Time series analysis

In this section, we explore the dynamic behavior of the liquidity and trading activity measures both at the aggregate market level and across rating categories using a simple Markov switching model. Given different economic and regulatory conditions throughout the sample period and their possible impact on the investors' risk tolerance and the dealers' risk taking capacity , it is reasonable to hypothesize that bonds of different credit risk may show different liquidity patterns in normal vs. distressed market conditions. This issue becomes particularly critical when we note that the vulnerable segments of the market may be the most affected during economic downturns or regulatory changes and can possibly act as a source of contagion for triggering systemic risk during severe liquidity shocks.

The current analysis also contributes to the recent growing literature on the impact of post-crisis regulations on the bond market liquidity. Particularly the "Volker Rule" of Dodd-Frank Act prohibits bank holding companies and their affiliates from engaging in risky proprietary trading and restricts bank ownership of hedge funds and private equity funds. Several market participant argue that the Volker Rule may have unintended consequences on dealers' liquidity provision, as it is very difficult to distinguish risky proprietary trading from normal market making activity (Duffie (2012)).

Few recent papers address these concerns: For example Bessembinder et al. (2016) Study dealer liquidity provision in the corporate bond market during the post-crisis period and find evidence that the Volker Rule has unintended adverse impact on market liquidity, as non-bank dealers are more willing to commit capital, complete block trades, hold inventory and trade on the principal basis on stressful days during the most recent years as compared to the pre-crisis period. Bao, O'Hara and Zhou (2016) Study the impact of Volker rule on corporate bond liquidity in periods of stressed market condition and find that bond liquidity deterioration around fallen angel downgrades has worsened following the implementation of the Volcker Rule.

The current analysis is distinguished from the previous studies in two ways. First, we examine the change in the market liquidity of Investment grade vs. high yield categories to capture the possibly different dynamic liquidity pattern for low risk versus riskier bonds. Second, the Markov switching model used for this analysis doesn't require making prior assumptions regarding the timing of regime changes, as opposed to diff-in-diff methods used in the previous studies. Given that it usually takes a long time for major regulations to become formally effective and their actual impacts on the financial markets may appear in advance of the formal compliance dates, it is very difficult to identify an exact date as the effective date of a regulation. For example the original effective date of the Volker rule was scheduled on July 21, 2012. However, implementation was delayed until an effective date of April 1, 2014, with the conformance period extended to July 21, 2015.

To obtain the monthly (il)liquidity time series, we calculate the bond level (il)liquidity measures in each month and calculate the monthly average across all bonds in our sample. Besides the liquidity and trading activity measures examined in the previous section, we analyze three more measures of dealers' capital commitment suggested by Bessembinder et al. (2016) to capture "the implicit costs associated with trades that were desired but not completed". In particular, the riskless principal trades

(RPTs) are considered as "effectively agency" trades that don't effectively influence the dealers' inventory. Hence a higher proportion of riskless principal trades (RPTs) in a month may imply dealers' reluctance to commit capital. Next, we consider the monthly percentage of block volume, to capture the difficulty of placing large orders. Finally, we examine the monthly percentage of dealer-to-dealer trades as opposed to the customer trades to captures interdealer market activity. Higher block volume and interdealer percentage may imply better liquidity conditions.

5.1 Markov-switching model estimation and results

The aggregate monthly liquidity and trading activity measures, $ILLIQ_t$ are modeled as non-linear $AR(k)$ processes that depend on their own past history, $ILLIQ_{t-1}, \dots, ILLIQ_{t-k}$ random shocks, δ_t and a discrete regime process, S_t, $S_t = \{1, \dots, n\}$

$$ILLIQ_t = \alpha_{s_t} + \phi_{1 s_t} ILLIQ_{t-1} + \dots + \phi_{k s_t} ILLIQ_{t-k} + \delta_{s_t} \varepsilon_t \quad \varepsilon_t \sim iid(0,1) \quad (4)$$

The switching regimes affect the intercept, α_{S_t} autocorrelation coefficients, $\emptyset_{1S_t}, \dots, \emptyset_{kS_t}$ and volatility, δ_{S_t} of the above process. The process governing the dynamics of the underlying regime S_t follows a first-order Markov chain, where the transition matrix is:

$$\Pi_{[i,j]} = \Pr(S_t = j \mid S_{t-1} = i) = p_{ij} \quad (5)$$

The Maximum Likelihood and EM algorithm of Gray (1996) are used to estimate the models' parameters and the regime probabilities. For model selection, AR(1) and AR(2) as well as simple Markov switching intercept models are considered as benchmarks and Markov switching AR(1) and AR (2) processes are examined based on their AIC and BIC criteria as well as their interpretability. Table 21 in Appendix B shows AIC and BIC for the various models examined for each liquidity tie series. The results show that all liquidity and trading activity time series can be sufficiently explained by Markov Switching $AR(k)$ processes with maximum order of 2 and maximum of 4 different regimes. The mean and variance for each regime can be obtained as follows. For the case of an *AR (1)* model, we have:

$$\mu_{S_t} = \frac{\alpha_{S_t}}{1-\phi_{1S_t}} \qquad Var_{S_t} = \frac{\delta_{S_t}^2}{1-\phi_{1S_t}^2} \quad (6)$$

For regime switching $AR(2)$ processes, the mean and variance for each regime are calculated as:

$$\mu_{S_t} = \frac{\alpha_{S_t}}{1-\phi_{1S_t}-\phi_{2S_t}} \qquad Var_{S_t} = \frac{1-\phi_{2S_t}}{1+\phi_{2S_t}} \times \frac{\delta_{S_t}^2}{(1-\phi_{2S_t})^2-\phi_{1S_t}^2} \quad (7)$$

The results of estimating the above model on liquidity and trading activity time series are reported in Table 7. For the purpose of this study, the mean and volatility of each regime have the most intuitive interpretation. To better interpret the results and understand the relation between the regimes governed by the unobserved Markov process and actual market events during the study period, we divide the sample into four periods and then calculate the proportion of each period that can be explained by each regime using the filtered probabilities. In particular, the period from July 2002 to November 2007 is considered as the pre-crisis period, December 2007 to June 2009 as the crisis period, July 2009 to June 2012 as the post-crisis period and July 2012 to September 2014 as the regulatory period. July 2012 is the original effective date of the

Volker rule and is similarly considered by Bessembinder et al. (2016) as the beginning of the regulatory period.

Panel A of Table 7 shows the results for the aggregate market liquidity and Panel B shows the results for the time series obtained by calculating the difference between the aggregate (il) liquidity of high yield and investment grade bonds. If the hypothesis regarding the different dynamic behavior of liquidity dimensions among risky and low risk bonds holds, we should observe changing regimes in these series.

For Amihud measure, the regime with highest mean and volatility forms 58% of the crisis period. The pre and post crisis periods are governed by the same regime of relatively low mean and standard deviation. Interestingly, we can see that the regime with the lowest mean and standard deviation almost completely overlaps with the regulatory period. The mean Amihud during the regulatory period is 0.30 which is lower than pre-crisis and post-crisis periods by 16 basis points. Figure 4 also demonstrates various regimes and their filtered probabilities for the Amihud measure. RTC, HW and RPT measures of bid-ask spread, show similar patterns. In particular for RTC, the regime with the highest mean (1.67) almost entirely happens during the crisis period and its intersection with other periods is negligible whereas the regime with the lowest mean (0.00) has its largest overlap with the regulatory period.

HW and RPT are best described by a two regime model where the regime with highest illiquidity clearly overlaps with the crisis period. Generally, the results for trading costs measures, indicate highly illiquid regime during the crisis period and do not provide any evidence of an increase in transaction costs following the crisis and particularly the most recent regulatory period.

Analyzing the trading activity time series, we observe two distinct regimes for the aggregate monthly number of trades. These regimes partially overlap with pre-crisis/crisis vs. post-crisis/regulatory periods with the higher mean and volatility regime covering almost the entire post-crisis and regulatory periods. The two regimes have mean difference of around 35. The standard deviation of the regime dominating pre-crisis/crisis periods is 3.37 compared to 9.76 for the other regime. The results for the Zero measure also shows an increase in trading activity and reduction in monthly zero trading days following the crisis. Generally, these results are indicative of an increase in trading activity during the recent periods. The results for the dealer's capital commitment measures show that for the percentage interdealer trades, the regime with the mean of 46.6% and standard deviation of 1.9% almost completely overlaps with the post-crisis and regulatory period and the regime with lower mean of 30.56% and higher standard deviation of 6.84% completely overlaps with the pre-crisis and crisis period. Results for the percentage block volume demonstrate a similar pattern. The percentage RPT trades show an increase during the recent regulatory period. Higher percentage of RPT trades may imply less dealers' willingness to provide liquidity by trading from their inventory and hence indicate deteriorating liquidity conditions. However the regime with the higher mean (8.05) only describes 20% of the regulatory period.

Panel B of Table 7 shows the results for the spread between the price impact and trading cost of high yield vs. investment grade bonds. While the Amihud measure is higher for the high yield bonds over the entire sample period, still a regime switching is observed with the wider spread regime dominating the crisis period and the narrower spread regime forming the major proportion of pre and post crisis periods and the entire regulatory period. These results imply that the price impact of investment grade and high yield bonds are converging more after the crisis and particularly during the regulatory period. Analyzing the bid-ask spread measures shows an interesting pattern. While the execution costs for investment grade bonds increases during the financial crisis, they actually decrease for the high yield bonds during the same period. For example, Figure 5 shows the regime changes for HW measure. As we can observe from Table7 and Figure 5, the regime with lower transaction costs for high yield bonds, forms 63% of the crisis period and the regime with higher positive mean mostly overlap with the pre-crisis and regulatory periods. Similar results are observed for RTC and RPT measures. This finding is consistent with the search and bargaining model of bid-ask spreads. Higher selling pressure of riskier bonds during the crisis period and lack of enough buyers relative to sellers adversely affects the bargaining power of bond dealers and reduces the bid-ask spreads charged for these bonds.

The trading activity spreads show two distinct regimes for the number of trades, both with negative means, which indicates lower mean number of trades for HY bonds for both regimes. However the regime with wider spread (mean of -5.58) covers 86% of the pre-crisis period and the regime with narrower spread covers 97% of the post-crisis and 88%of the regulatory period which shows that the aggregate monthly number of HY bond trades is increasing with respect to the IG trades in recent periods. The measures of dealers' capital commitment show the following patterns: The mean percentage of RPT trades is becoming larger for HY bonds compared to IG bonds during the regulatory period by around 5.2%. This result provides evidence of dealers becoming more reluctant to conduct principal transactions for riskier bonds during the regulatory period. However the findings from the other two measures do not show evidence of less liquidity provision for riskier bonds following the crisis, as the percentage of interdealer trades in HY bonds have become higher after the crisis and particularly during the regulatory period. %block volume for HY bonds for this period is comparable to pre-crisis and is smaller than the %block volume for the IG category.

6. Robustness tests

We test the robustness of the results on a subsample of top bonds for each issuer as they attract most of the trading activity. Ronen and Zhou (2013) define the bond with the highest institutional trade volume immediately following an earnings announcement (and before NYSE market open) as the top bond for the firm. Based on their findings some bonds attract more order flow than others after earnings announcement, with distinct patterns of large institutional trades clustering in one or few bonds issued by the same firm. They suggest that top bonds have the following characteristics most of the time and can be predicted ex ante based on these characteristics: Have the longest original maturity among the bonds issued by the same firm, are the most recently issued, have at least one attached embedded option, have relatively high offering amount, are one of the issuer's three most liquid bonds, are the issuer's highest rated bonds. We use the above characteristics (except having embedded options[12]) to identify the top bonds of each issuer on a monthly basis that

[12] In the data filtering stage the bonds with embedded options like call and put options are removed from the sample so we didn't consider this characteristic in my procedure of estimating top bonds.

form around 73% of our sample of bonds.[13] We also construct a sample consisting of a single top bond for each issuer in the following way: for each issuer, we identify the bond that has been in the “top” role during a longer period (the bond that has the maximum number of months as a top bond). The unique top bonds estimated this way form around 32% of our sample. We repeated the regressions on these subsamples and the results are generally robust.

We also repeated the regressions on two subsample of retail size and institutional size trades and found qualitatively similar results. [14]

7. Conclusion

In this paper, we use more than twelve years of bond transaction data from TRACE to conduct a comprehensive investigation of how liquidity and trading activity of corporate bonds vary with their credit ratings and how the dynamic behavior of this relationship changes over time.

Our main finding is that unlike the implications of traditional microstructure model, the trading costs as measured by bid-ask spreads do not increase monotonically with credit risk. Instead, we find and inverted U-shaped relationship over the entire sample where the bid-ask spreads increase with credit risk for investment grade bonds but decline gradually after we cross the investment grade / high yield boundary. Moreover studying the dynamics of this relationship using panel regressions over three subsamples shows that trading costs become more negatively related to ratings as we move to riskier bonds following and particularly during the financial crisis.

[13] The “top” role for an issuer’s bond shifts across issues over time with around 60% shift their role after one announcement and around 90% maintain their position for at most three quarters.
[14] . Results from the robustness tests are non reported but are available from the authors upon request.

Further, we examine the liquidity of investment grade vs. high yield categories by modeling the monthly aggregate liquidity and trading activity time series as Markov switching AR(k) processes. The results show that during the normal periods, the aggregate transaction costs for riskier bonds is higher compared to low risk bonds, however this relationship demonstrate an abrupt regime change during the crisis period: while the spreads increase dramatically for investment grade bonds, they stay relatively invariant for HY bonds.

These results can possibly be explained in light of a search based framework in which bond dealers actively search for trading counterparty to mitigate their holding period risk or even don't take inventory risk until they find the opposite side of the trade, particularly during liquidity shocks. Recent empirical evidence supports this explanation. This may undermine the informativeness of bid-ask spreads as an appropriate measure of liquidity for the most risky segments of the markets or during periods of market distress and highlight the importance of other measures that better reflect the cost of liquidity and dealers capital commitment. Narrowing our focus to bid-ask spreads to gauge market liquidity for some type of securities may be a case of being "penny wise and pound foolish".

References

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets* 5, 31–56.

Bao, Jack, Jun Pan, and Jiang Wang, 2011, The illiquidity of corporate bonds. *The Journal of Finance* 66(3), 911–946.

Bao, Jack, Maureen O'Hara, and Alex Zhou, 2016, The Volker Rule and market-making in times of stress, Working paper, Board of Governors of The Federal Reserve.

Bessembinder Hendrik, William Maxwell, Kumar Venkataraman, 2006, Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. *Journal of Financial Economics* 82, 251–288.

Bessembinder, Hendrik, Stacey E. Jacobsen, William F. Maxwell, and KumarVenkataraman, 2016, Capital Commitment and Illiquidity in Corporate Bonds, SSRN working paper.

Bessembinder, Hendrik, and William Maxwell, 2008, Markets: transparency and the corporate bond market, *Journal of Economic Perspectives* 22(2), 217-234.

Brunnermeier, M., and Lasse Heje Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22(6), 2201-2238.

Chakravarty, Sugato, and Asani Sarkar, 2003, Trading costs in three U.S. bond markets, *Journal of Fixed Income* 13, 39-48.

Chen, Hui, Rui Cui, Zhiguo He, Konstantin Milbradt, 2015, Quantifying liquidity and default risks of corporate bonds over the business cycle, NBER Working Papers 20638.

Dick-Nielsen, Jens, 2014, How to clean enhanced TRACE data, Working paper, SSRN. http://ssrn.com/abstract=2337908.

Dick-Nielsen, Jens, Peter Feldhütter and David Lando, 2012, Corporate bond liquidity before and after the onset of the subprime crisis, *Journal of Financial Economics* 103(3), 471 –492.

Duffie, Darrell, Nicolae Gârleanu, and Lasse Heje Pedersen, 2005, Over-the-counter markets, *Econometrica* 73(6), 1815–1847.

Duffie, Darrell,2012, Market making under the proposed Volker rule, Rock Center for Corporate Governance at Stanford University, Working Paper No.106.

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate bond market transaction costs and transparency. *Journal of Finance* 62, 1421–1451.

Feldhütter, Peter, 2012, The same bond at different prices: identifying search frictions and selling pressures, *Review of Financial Studies* 25(4),1155–1206.

Glosten, L., and P. Milgrom, 1985, Bid, ask, and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71-100.

Goldstein, Michael A., Edith S. Hotchkiss, and Erik R. Sirri, 2007, Transparency and liquidity: A controlled experiment on corporate bonds. *Review of Financial Studies* 20, 235–273.

Goldstein, Michael A., and Edith S. Hotchkiss, 2017, Dealer behavior in highly illiquid risky assets, working paper.

Gray, Stephen F., 1996, Modeling the conditional distribution of interest rates as a regime switching process, *Journal of Financial Economics* 42, 27-62.

Grossman, Sanford J., and Merton H. Miller, 1988, Liquidity and market structure, *Journal of Finance* 43 (3), 617-633.

Hamilton, David T., and Richard Cantor, 2004, Rating transition and default rates conditioned on outlooks, *Journal of Fixed Income* 14, 54-70.

Han, Song, and Hao Zhou, 2008, Effects of liquidity on the non default component of corporate yield spreads: Evidence from Intraday Transactions Data, Available at http://ssrn.com/paper=946802.

Harris, Lawrence E., and Michael S. Piwowar, 2006, Secondary trading costs in the municipal bond market, *The Journal of Finance* 61, 1361–1397.

Harris, Lawrence, 2015, Transaction costs, trade throughs, and riskless principal trading in corporate bond markets, Working Paper, University of Southern California.

He, Zhiguo, and Konstantin Milbradt, 2014, Endogenous liquidity and defaultable bonds, NBERWorking Papers 18408.

Ho, Thomas, 1981, Optimal dealer pricing under transactions and return uncertainty, *Journal of Financial Economics* 9, 47-73.

Ho, Thomas, and Hans Stoll, 1983, The dynamics of dealer markets under competition, *The Journal of Finance* 38, 1053-1074.

Hong, Gwangheon, and Arthur Warga, 2000, An empirical study of bond market transactions, *Financial Analysts Journal* 56, 32-46.

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53(6), 1315-1336.

Lesmond, David A., Joseph P. Ogden, and Charles A. Trzcinka, 1999, A new estimate of transaction costs, *The Review of Financial Studies* 12:1113-1141.

Mizrach, Bruce ,2015,Analysis of corporate bond liquidity, Research note, FINRA.

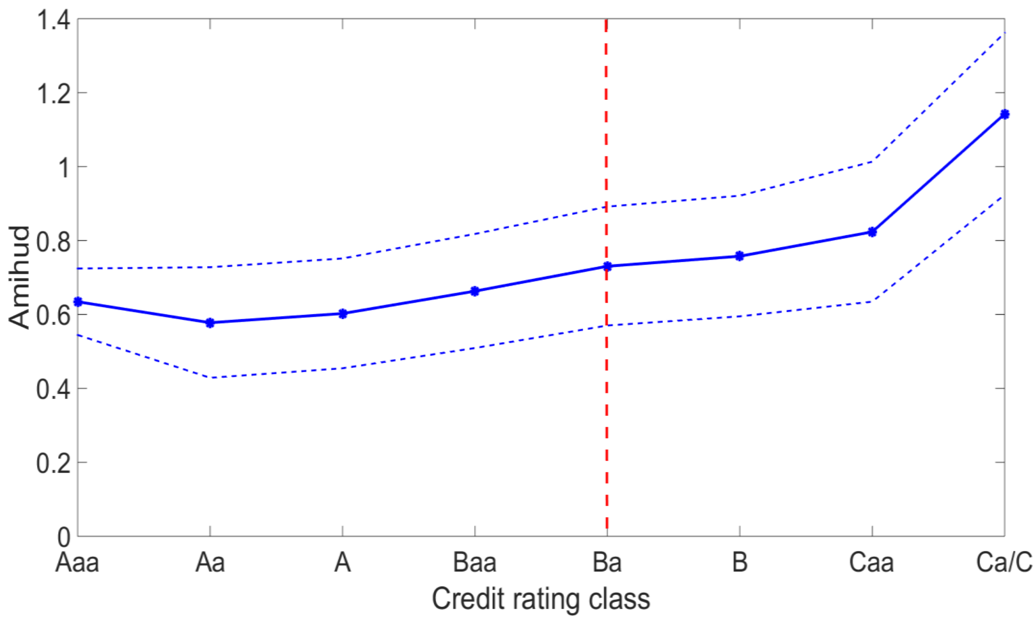
Ronen, Tavy, and Xing Zhou, 2013, Trade and information in the corporate bond market, *Journal of Financial Markets* 16, 61-103.

Schultz, Paul, 2001, Corporate bond trading costs: a peek behind the curtain, *Journal of Finance* 56, 677-698.

Stoll, Hans R., 1978, The supply of dealer services in securities markets, *Journal of Finance* 33, 1133-1151.

Figure1: Expected liquidity across credit ratings after controlling for other relevant variables (All proxies except #Trades and Volume measure illiquidity; Dashed lines show 95% confidence intervals)

Panel A: Amihud



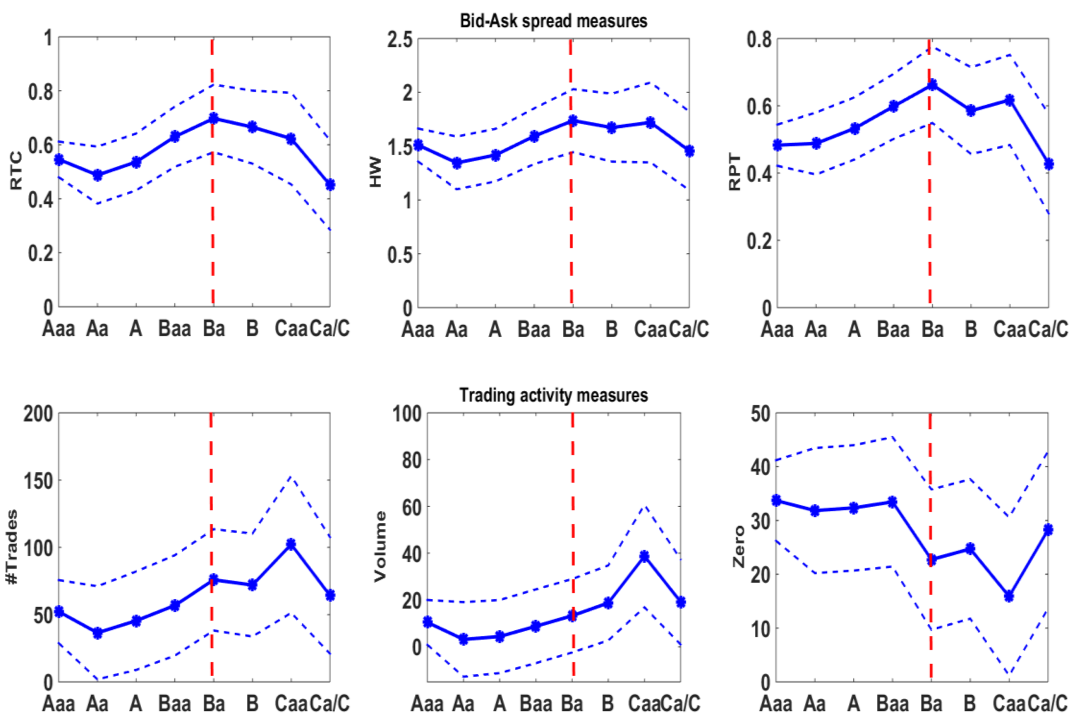
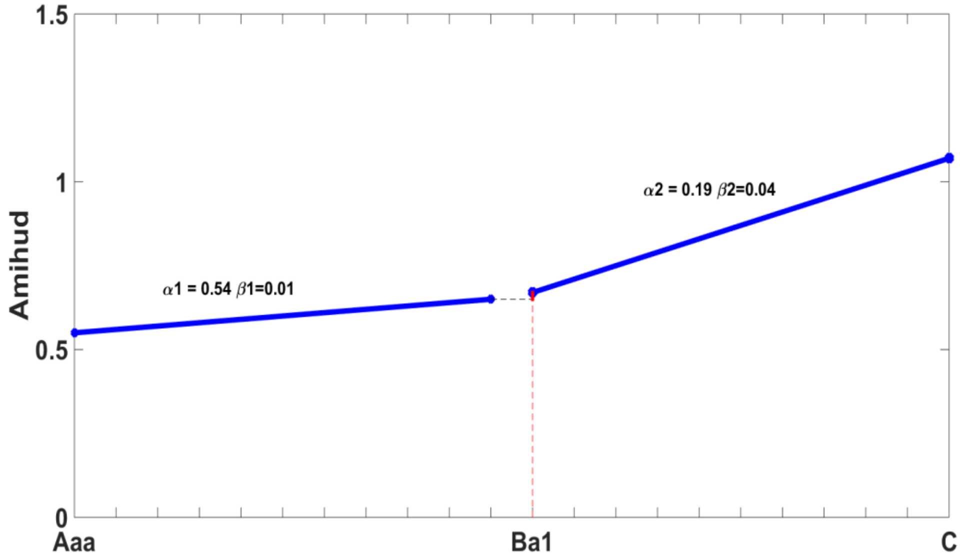


Figure2: Visualizing piecewise regression results
(The numbers on each line show the intercept and the slope)
Panel A: Amihud



Panel B: Bid-ask spread and trading activity measure

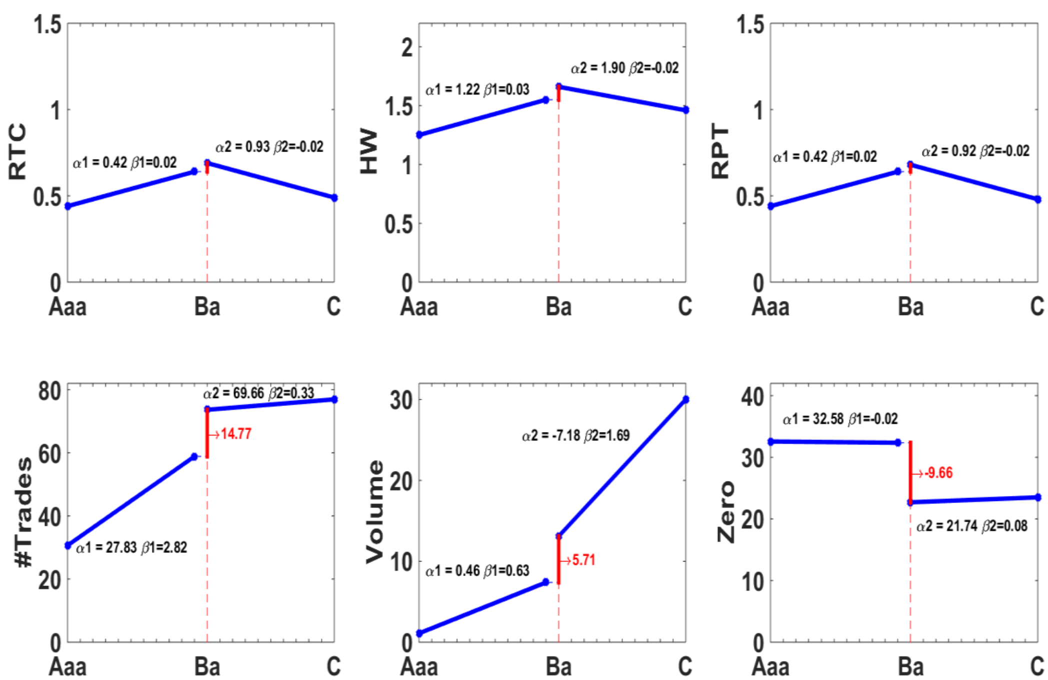
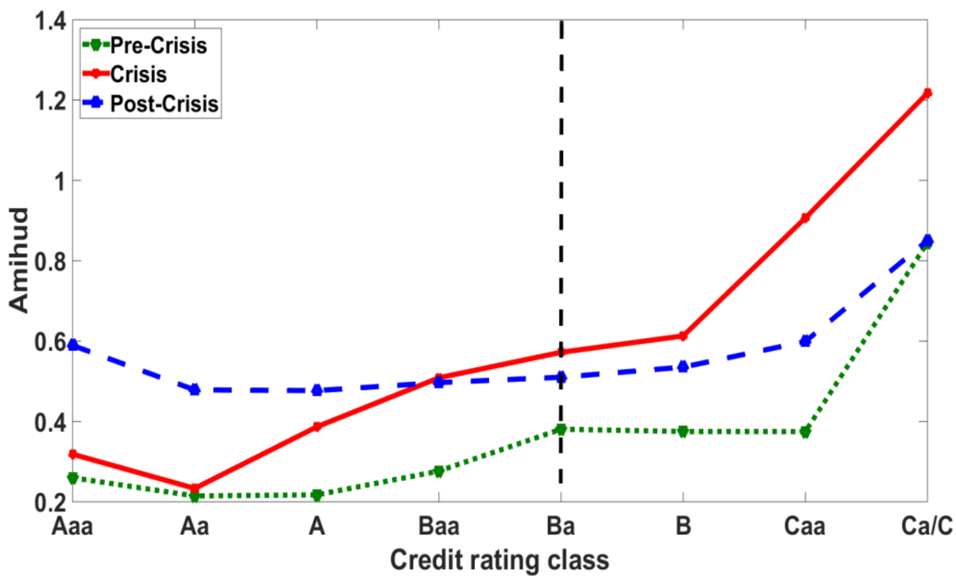


Figure3:

Expected liquidity across credit ratings before, during and after the financial crisis

Panel A: Amihud



Panel B: RTC

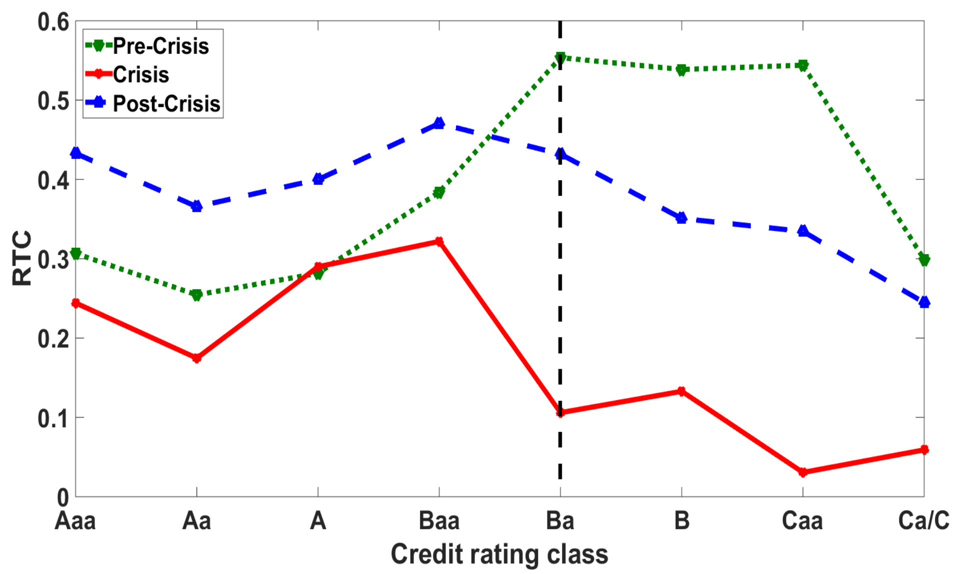


Figure 4:

Regime changes for the aggregate market Amihud measure and the filtered probabilities for each regime

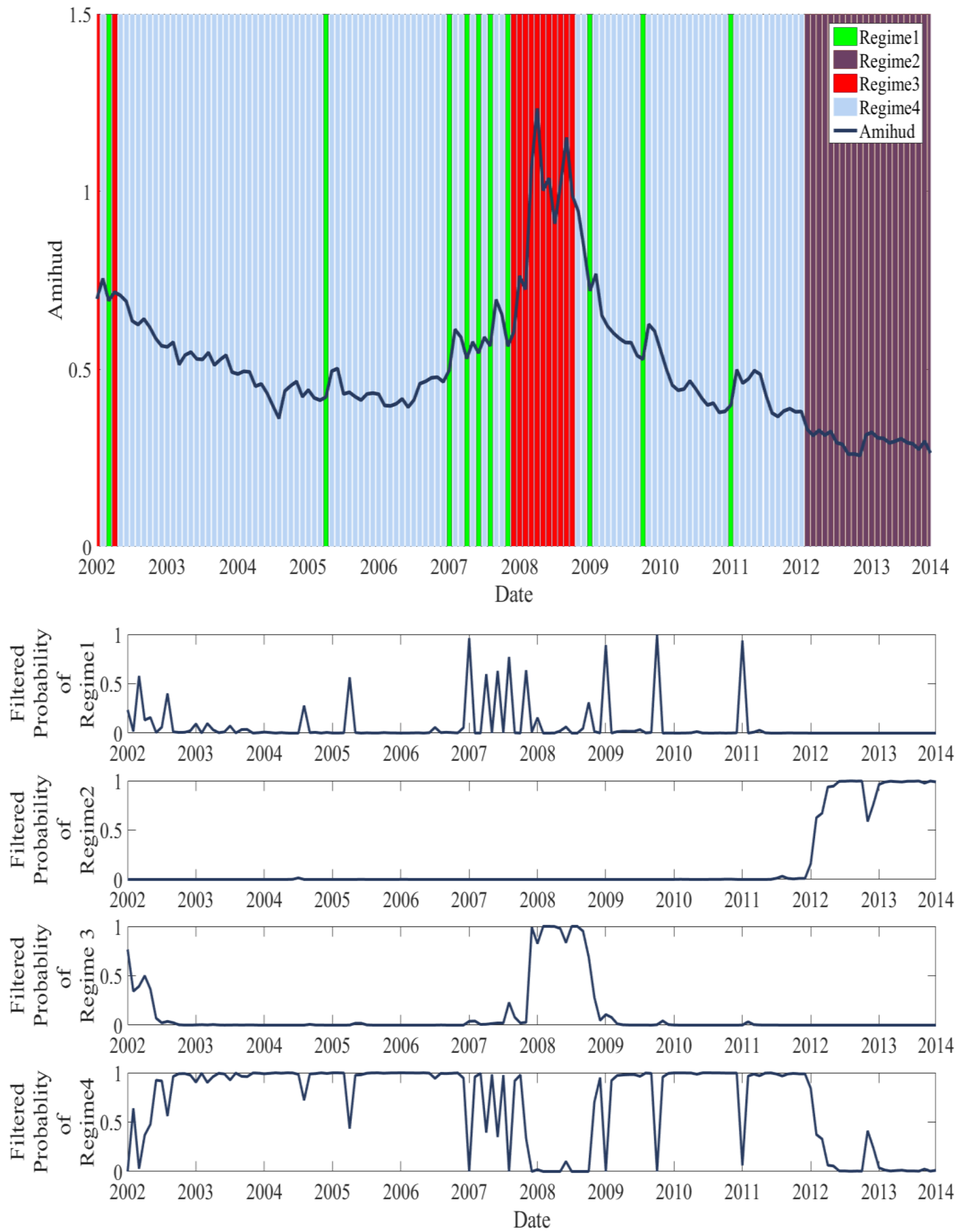


Figure5:

Regime changes for HY vs. IG aggregate bid-ask spread (as proxied by HW) measure and the filtered probabilities for each regime

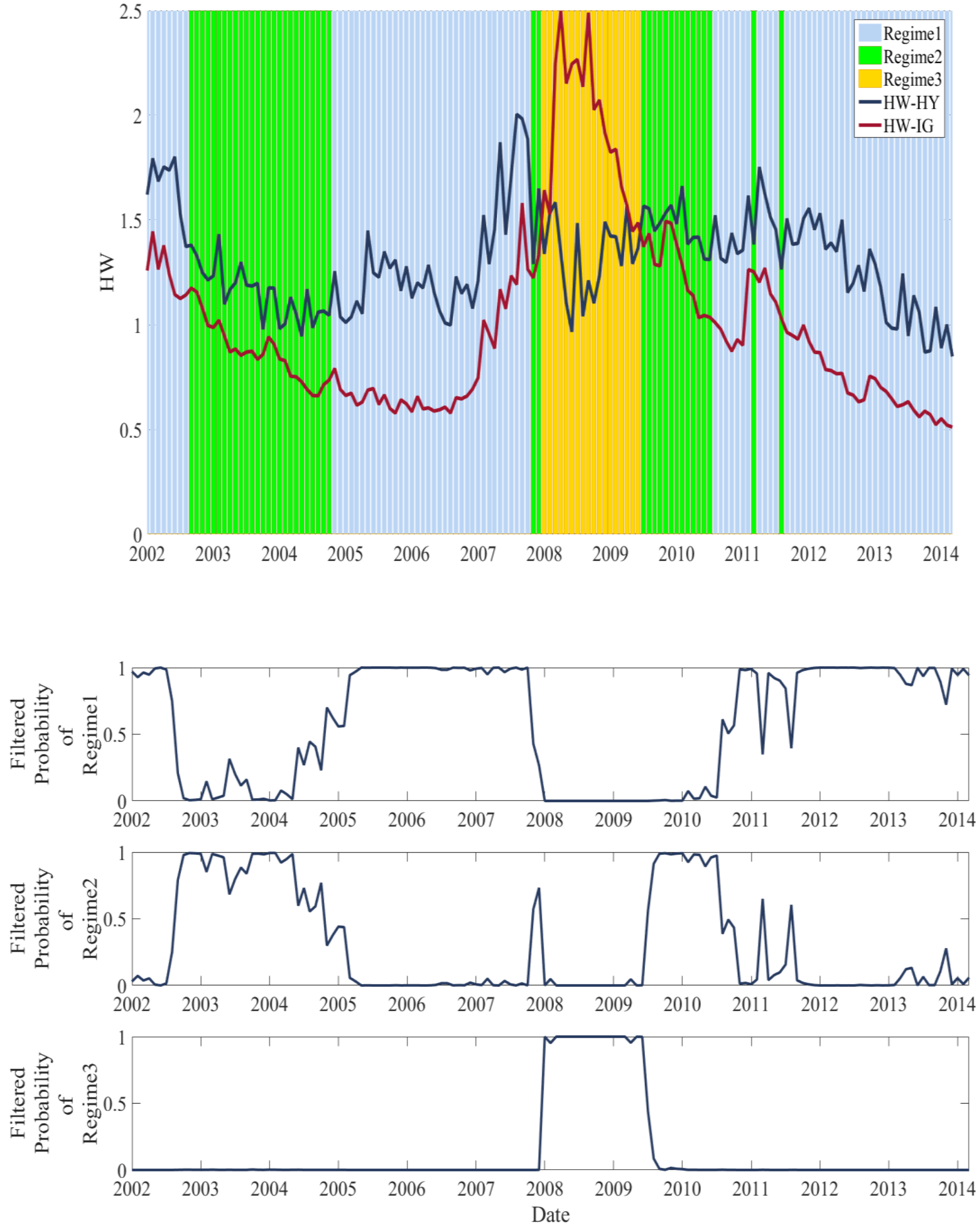


Table 1: Data filtering steps

This table shows the number of observations in original Enhanced TRACE and Mergent FISD datasets as well as the number of observations left and percentage of omitted observations after each step of the filtering process. *#bonds* is the number of bond issues, *# trades* Is the number of transactions. *%Omitted*, is the omitted bonds in each step as a percentage of the original sample. For FISD data, *% Omitted* is bonds omitted in each step as a percentage of all corporate bonds that exist in the original sample period for at least one year with non-missing offering date and price.

Panel A: Enhanced TRACE filtering process			
Original Enhanced TRACE sample	*# bonds*	*# trades*	*% Omitted*
	112,879	**141,997,423**	**-**
Dick-Nielsen filter:			
– Same-day corrections and cancelations	112,482	135,798,340	0.35
– Reversals and the matching original transaction report	112,378	133,557,702	0.09
– Agency transactions where the principal transaction has the same price as the agency transaction	107,629	126,469,001	4.21
– One of the reports in each interdealer transaction pair and trades that are not secondary market, special circumstances, commissioned , odd number of days to settlement, automatic give up and noncash trades	87,221	86,542,005	18.08
Median and reversal filter:			
– 20% daily median and 50% reversal	**87,159**	**86,450,187**	0.05

Panel B: FISD filtering process			
Original FISD sample*	*#bonds*	*#firms*	*% Omitted*
	325,810	13,381	**-**
Bonds that exist in the sample for at least one year with non-missing offering date and price	**87,032**	**8,653**	**-**
Exclude:			
– Secured	87,001	8,646	0.04
– Variable rate and zero coupon	47,142	8,070	**45.80**
– Non US dollar denominated and/or foreign issuer	33,188	6,072	**16.03**
– Credit enhancement	29,687	5,717	4.02
– Convertible	27,975	4,960	1.97
– Asset backed	27,446	4,914	0.61
– Preferred	26,947	4,913	0.57
– Fungible	22,023	4,676	5.66
– Exchangeable	17,160	3,911	5.59
– Callable	7,018	1,346	**11.65**
– Putable	6,786	1,326	0.27
– Unit-deal	6,783	1,323	0.00
– Industry group: not industry, finance or utility	6,766	1,313	0.02
– Non-rated or rating type not FR,MR SPR	**6,549**	**1,271**	0.25

Panel C: Additional filtering and observations by liquidity proxy			
Merged TRACE-FISD*	**7,988,836**	**4,065**	**1,187**
– Exclude bonds that are traded less than 4 days and less than two times during each trading day	**7,640,266**	**3,909**	**1,173**

Table 2: Summary statistics

This table reports summary statistics for our sample of bonds by year. *# Bonds* is the number of bonds that exist in the sample during each period. *Issue size* is the bond's face value issued in millions of dollars. *Coupon* is the bond coupon payment in percent. *Maturity* is the bond's time to maturity in years. *Age* is the time since issuance in years. *Rating* is the average of numerical translation of Moody's, Standard and Poor's and Fitch rating: 1=Aaa/AAA, 21=C. *Price* is the average market value of the bond in dollars. # Issuer bonds, is the number of bonds issued by each firm.

	#Bonds	Issue size (M)		Coupon		Maturity		Age		Ratings		Price		# Issuer bonds	
		Mean	*Med*	*Mean*	*Med*	*Mean*	*Med*	*Mean*	*Med*	*Mean*	*Med*	*Mean*	*Med*	*Mean*	*Med*
Panel A: Summary statistics by year after imposing all filtering steps															
2002	3152	141	100	7.1	7.0	6.5	3.6	6.5	6.7	7.0	6.3	102	105	7.8	4
2003	3293	147	100	7.0	7.0	5.8	3.0	6.9	7.1	7.2	6.3	105	106	8.0	4
2004	3039	242	100	6.9	7.0	5.5	2.7	7.5	7.9	7.0	6.0	106	105	8.5	4
2005	2604	269	100	6.8	6.9	5.8	2.8	8.0	8.7	6.9	6.0	104	103	9.3	5
2006	2135	302	100	6.7	6.9	6.3	2.8	8.5	8.9	6.8	6.0	102	101	10.0	5
2007	1826	359	125	6.6	6.8	6.7	3.1	9.0	9.4	6.6	6.0	103	101	10.6	5
2008	1574	416	150	6.6	6.8	7.0	3.7	9.7	9.9	6.6	6.0	98	100	11.6	6
2009	1290	487	150	6.7	7.0	7.7	4.3	10.3	11.1	7.3	6.1	97	101	11.9	5
2010	1159	573	150	6.6	7.0	8.0	4.9	10.8	12.1	7.6	6.3	104	105	11.9	5
2011	1071	661	200	6.5	6.9	8.0	5.2	11.3	13.1	7.5	6.3	105	106	12.7	6
2012	1104	672	200	6.0	6.6	7.7	5.2	10.7	11.8	7.4	6.6	109	106	14.5	6
2013	1054	702	178	5.7	6.3	7.8	5.3	10.6	9.9	7.2	7.0	110	107	18.2	6
2014	935	741	175	5.7	6.5	7.9	6.1	11.4	11.1	7.2	7.0	111	108	19.2	6
Panel B: Summary statistics by year before imposing FISD filtering steps															
2002	14831	209	105	6.8	6.9	8.0	5.1	4.2	3.6	8.6	8	95	100	4.0	1
2003	19054	191	100	6.3	6.5	8.0	5.0	3.7	2.4	8.1	7	99	101	4.7	1
2004	20804	184	50	5.8	5.9	8.2	5.3	3.3	1.8	7.7	7	101	100	5.2	1
2005	21698	182	35	5.6	5.5	8.1	5.3	3.4	2.0	8.2	8	99	100	5.5	1
2006	22016	193	30	5.5	5.5	8.1	5.2	3.6	2.4	7.7	6	98	98	5.7	1
2007	22750	201	24	5.4	5.5	8.2	5.2	3.7	2.8	6.9	5	98	99	6.1	1
2008	22444	206	17	5.1	5.4	8.0	5.0	3.9	3.2	9.1	7	91	95	6.7	2
2009	21384	239	24	5.1	5.5	7.9	4.8	4.3	3.6	8.4	7	89	96	6.5	2
2010	21802	254	29	5.0	5.4	7.9	5.0	4.2	3.4	8.6	8	99	100	6.2	2
2011	21829	266	32	4.8	5.3	7.9	5.0	4.2	3.2	8.0	7	100	100	6.2	2
2012	24448	254	22	4.3	4.8	7.2	4.4	3.9	2.1	8.1	7	103	101	7.0	2
2013	21888	259	23	4.0	4.3	6.9	4.1	4.1	2.3	8.6	8	109	102	6.8	2
2014	16355	302	70	4.1	4.4	7.2	4.2	4.9	3.1	8.6	8	112	104	5.8	2

Table 2 (continued): Summary statistics

This table reports summary statistics for our sample of bonds by year. *# Bonds* is the number of bonds that exist in the sample during each period. *Issue size* is the bond's face value issued in millions of dollars. *Coupon* is the bond coupon payment in percent. *Maturity* is the bond's time to maturity in years. *Age* is the time since issuance in years. *Rating* is the average of numerical translation of Moody's, Standard and Poor's and Fitch rating: 1=Aaa/AAA, 21=C. *Price* is the average market value of the bond in dollars. # Issuer bonds, is the number of bonds issued by each firm.

	#Bonds	Issue size (M)		Coupon		Maturity		Age		Ratings		Price		# issuer bonds	
		Mean	*Med*	*Mean*	*Med*	*Mean*	*Med*	*Mean*	*Med*	*Mean*	*Med*	*Mean*	*Med*	*Mean*	*Med*
Panel C: Summary statistics by rating group for the cleaned sample															
≥AA/Aa	1154	555	175	6.1	6.5	5.6	3.6	5.2	5.1	3.7	4.0	103	102	14.5	8
A;BBB/Baa	2924	347	100	6.4	6.7	6.3	3.9	5.6	5.6	6.8	6.0	103	102	13.5	5
BB/Ba; B	495	195	125	7.1	7.1	7.1	3.0	7.0	6.8	12.0	12.0	96	99	7.7	3
≤CCC/Caa	190	227	150	7.7	7.7	8.0	4.3	9.1	9.4	17.7	17.0	72	82	5.6	4
Total	3909	351	100	6.7	6.9	6.6	3.5	8.6	8.3	7.1	6.3	104	104	32	4

Table 3: Statistics for liquidity measures

This table shows statistics for corporate bond liquidity measures. The measures are calculated monthly for each bond using corporate bond transactions data from TRACE during the period from July 2002 to September 2014. There are a total of 3909 bond issues and 1173 bonds issuers in our sample during this period. Panel A shows quintiles for the liquidity measures. Panel B shows the correlation among the measures.

Panel A: Summary statistics for liquidity measures

	Amihud	*RTC*	*HW*	*RPT*	*Volume*	*# trades*	*Zero (%)*
Mean	0.57	0.65	1.34	0.67	14.18	32	74
95th	1.99	1.90	4.01	1.74	64.40	145	100
75th	0.75	0.88	1.91	0.92	5.5	23	100
50th	0.32	0.47	0.88	0.52	0.10	3	90
25th	0.09	0.21	0.35	0.28	0.00	0	53
5th	0.00	0.01	0.02	0.12	0.00	0	0

Panel B: Correlation matrix for liquidity measures

	Amihud	*RTC*	*HW*	*RPT*	*Volume*	*#trades*	*Zero (%)*
Amihud	1.00						
RTC	0.54^{***}	1.00					
HW	0.58^{***}	0.65^{***}	1.00				
RPT	0.32^{***}	0.50^{***}	0.37^{***}	1.00			
Volume	-0.11^{***}	-0.07^{***}	-0.13^{***}	0.00	1.00		
#trades	-0.01	0.05^{***}	-0.01	0.06^{***}	0.50^{***}	1.00	
Zero	0.06^{***}	0.14^{***}	0.12^{***}	-0.00	-0.25^{***}	-0.41^{***}	1.00

Panel C: Mean liquidity measures by rating groups

	Amihud	*RTC*	*HW*	*RPT*	*Volume*	*#trades*	*Zero (%)*
≥AA/Aa	0.49	0.54	1.08	0.61	19.06	39	68.37
A;BBB/Baa	0.56	0.66	1.36	0.67	12.94	31	74.48
BB/Ba; B	0.74	0.87	1.82	0.81	12.81	35	69.38
≤CCC/Caa	0.85	0.64	1.45	0.67	17.51	28	79.07

Table 4: Panel regressions for liquidity proxies.

This table reports coefficient estimates for monthly panel regressions of various liquidity proxies on credit rating dummies controlling for issue level and issuer level characteristics. The dependent variables are *Amihud, RTC, HW, RPT, #Trades, Volume, Zero* for column 2 to 7 respectively, as defined in the text. Aa/AA,…,C are dummy variables equal to one if Moody's rating class for the bond is Aa (Aa or Aa2 or Aa3),…C, and zero otherwise. If the bond is not rated by Moody's, S&P rating is used. Control variables are defined both in Table 2 and the text. *Utility* is a dummy variable equal to one, if the issuer belongs to utility industry group and zero otherwise. *Finance* is a dummy variable equal to one if the issuer is a financial firm and zero otherwise.

	Price impact	Bid-ask spread			Trading activity		
	Amihud	RTC	HW	RPT	#Trades	Volume	Zero
Rating dummies:							
Aa/AA	-0.06*	-0.06**	-0.17***	0.00	-15.78***	-7.28**	-1.88
A	-0.03	-0.01	-0.09**	0.05***	-6.78	-6.06**	-1.38
Baa/BBB	0.03	0.08***	0.08	0.12***	4.60	-1.65	-0.26
Ba/BB	0.10***	0.15***	0.23***	0.18***	23.59***	2.81	-10.98***
B	0.12***	0.12***	0.16*	0.10***	19.73***	8.30**	-9.00***
Caa/CCC	0.19***	0.07	0.21*	0.13***	49.97***	28.33***	-17.82***
Ca/CC/C	0.51***	-0.09*	-0.05	-0.05	11.98	8.74**	-5.49
Bond/firm controls:							
Trade size	-0.00***	-0.00	-0.00	0.00	-0.10**	5.80***	0.05***
% Inst. trades	-0.97***	-0.62***	-1.91***	-0.34***	-72.94***	8.39**	18.32***
Maturity	0.02***	0.02***	0.06***	0.02***	-0.40***	0.01	0.23***
Coupon	0.03***	0.04***	0.06***	0.02***	-2.79***	-2.15***	2.60***
Age	0.00	-0.00**	0.01**	-0.01***	0.05	-0.20	0.20
Issue size	0.06***	0.03***	-0.10***	0.07***	180.50***	94.42***	-36.19***
Coupon freq.	0.01**	0.01***	0.00	0.01	-2.30***	0.59***	3.14***
# Issuer bonds	-0.00***	0.00***	0.00***	0.00*	0.75***	0.16***	-0.02
Utility	0.09***	0.10	0.04	-0.04	-3.20	2.48**	10.98***
Finance	0.05***	0.00	0.04	-0.01	3.00	-0.85	-3.54***
Intercept	0.63***	0.55***	1.51***	0.48***	52.25***	10.44**	33.71***
Year fixed effect	Y	Y	Y	Y	Y	Y	Y
# Bonds	3,478	3,379	3,082	2,450	3,478	3,478	3,478
Obs	129,573	120,660	93,977	61,567	129,573	129,573	129,573
Adjusted R^2	0.22	0.20	0.36	0.16	0.32	0.37	0.38

*indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the1% level.

Table 5: Piecewise panel regressions.

This table reports the coefficient estimates for piecewise monthly panel regressions for various liquidity proxies. The regression model is in the following form:

$$ILLIQ_{it} = \alpha_1 + \delta_k + \alpha_2 Junk_{it} + \beta_1 Rating_{it} + \beta_2 Junk_{it} \times (Rating_{it} - 11) + \boldsymbol{Controls}_{it} + \varepsilon_{it}$$

Rating is the numerical translation of Moody's rating: 1=Aaa, 21=C. *Junk* is a dummy variable equal to one if the Moody's rating for the bond is between 11=Ba to 19=Caa and equal to zero if the rating for the bond is investment grade. δ_k denotes the year fixed effect. $\boldsymbol{Controls}_{it}$ denotes the matrix of control variables. The t-statistics are calculated using heteroscedasticity and autocorrelation robust standard errors. *indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

	Price impact	Bid-ask spread			Trading activity		
	Amihud	RTC	HW	RPT	#Trades	Volume	Zero
Rating (β_1)	0.01***	0.02***	0.03***	0.02***	2.82***	0.63**	-0.02
	(3.91)	(8.90)	(6.16)	(9.28)	(4.06)	(2.55)	(-0.10)
Junk (α_2)	-0.02	0.07**	0.13**	0.06**	14.44***	4.02**	-9.74***
	(-0.70)	(2.53)	(2.09)	(2.26)	(2.86)	(2.55)	(-4.64)
Junk×(Rating-11)(β_2)	0.03***	-0.04***	-0.05***	-0.04***	-2.49**	1.06**	0.10
	(4.20)	(-7.25)	(-4.52)	(-6.63)	(-2.15)	(2.24)	(0.22)
Intercept (α_1)	0.54***	0.42***	1.22***	0.42***	27.83**	0.46	32.58***
	(13.78)	(13.47)	(17.38)	(14.48)	(2.42)	(0.11)	(9.43)
Controls	Y	Y	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y	Y	Y
# Bonds	3,478	3,379	3,082	2,450	3,478	3,478	3,478
Obs	129,573	120,660	93,977	61,567	129,573	129,573	129,573
Adjusted R^2	0.21	0.20	0.36	0.16	0.32	0.37	0.37

Table 6: Panel regressions for liquidity proxies during three sub-periods

This table reports coefficient estimates for monthly panel regressions of various liquidity proxies on credit rating dummies controlling for issue level and issuer level characteristics, over three sub-periods. *Pre-crisis* is the sample period from Jul. 2002 to Nov. 2007, *crisis* is the period from Dec. 2007 to June 2009, *post-crisis* is the period from July 2009 to Sep.2014. Dependent variables, rating dummies and control variables are similar to Table4. To save space, the coefficients for control variables are not reported in the table.

	Price impact	Bid-ask spread			Trading activity		
	Amihud	*RTC*	*HW*	*RPT*	*#Trades*	*Volume*	*Zero*
Panel A: Pre-crisis period							
Aa/AA	-0.05	-0.05**	-0.09*	0.01	-9.4**	-4.2	-4.1*
A	-0.04	-0.03	-0.07	0.03	3.5	-2.3	-4.9**
Baa/BBB	0.02	0.08***	0.11**	0.09***	14.0**	2.5	-1.2
Ba/BB	0.12***	0.25***	0.33***	0.25***	21.5***	4.7	-11.0***
B	0.12***	0.23***	0.35***	0.22***	21.2***	7.8**	-10.6***
Caa/CCC	0.11**	0.24***	0.39***	0.20***	54.5***	40.9***	-22.2***
Ca/CC/C	0.59***	-0.01	0.13	0.01	22.4***	16.1***	-9.8***
Intercept	0.26***	0.31***	0.79***	0.40***	29.5***	-6.9	44.3
# Bonds	3,041	2,946	2,708	2,042	3,041	3,041	3,041
Obs	80,033	72,639	57,788	29,777	80,033	80,033	80,033
Adjusted R^2	0.21	0.21	0.30	0.14	0.23	0.36	0.40
Panel B: Crisis period							
Aa/AA	-0.08	-0.07	-0.10	0.02	-34.0	-5.0	0.05
A	0.07	0.05	0.20**	0.10***	-20.4	0.5	-4.6
Baa/BBB	0.19**	0.08	0.49***	0.09***	-9.5	6.5	-3.2
Ba/BB	0.25**	-0.14*	0.34	0.02	-0.7	8.5	-10.1*
B	0.30***	-0.11*	-0.19	0.03	0.8	14.0*	-4.9
Caa/CCC	0.59***	-0.21***	-0.01	-0.14**	33.3	22.3***	-18.0***
Ca/CC/C	0.90***	-0.18*	-0.19	-0.17*	5.4	14.1	-11.7**
Intercept	0.32**	0.24**	1.14***	0.23***	-18.71	-37.6***	49.3***
# Bonds	1,134	1,125	1,012	901	1,134	1,134	1,134
Obs	12,772	12,351	9,133	7,221	12,772	12,772	12,772
Adjusted R^2	0.19	0.17	0.25	0.21	0.31	0.49	0.40
Panel C: Post-crisis period							
Aa/AA	-0.11	-0.07	-0.60***	-0.03	24.27**	-4.64	-9.80
A	-0.11	-0.03	-0.59***	0.00	12.47	-5.94	-8.62
Baa/BBB	-0.09	0.04	-0.54***	0.06	17.23**	-2.89	-10.91*
Ba/BB	-0.08	0.00	-0.48***	0.06	60.23***	5.54	-24.43***
B	-0.05	-0.08	-0.65***	-0.06	49.89***	16.5***	-18.90***
Caa/CCC	0.01	-0.10	-0.75***	0.01	76.02***	18.3***	-18.17**
Ca/CC/C	0.26***	-0.19**	-0.66***	-0.12**	49.80***	7.92	-12.55
Intercept	0.59***	0.43***	2.02***	0.36***	40.53*	17.85**	41.91***
# Bonds	1,203	1,192	1,068	1,029	1,203	1,203	1,203
Obs	36,768	35,670	27,056	24,569	36,768	36,768	36,768
Adjusted R^2	0.22	0.19	0.42	0.13	0.36	0.34	0.40

*indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table 7: Parameters of Markov switching models for monthly liquidity and trading activity time series.

This table reports the estimated parameters of the Markov switching models for monthly liquidity and trading activity time series and the proportion of each regime in each of the pre-crisis: Jul. 2002 to Nov. 2007, crisis: Dec. 2007 to June 2009, post-crisis: July 2009 to June 2012, and regulatory period: Jul. 2012 to Sep.2014. Panel A shows these values for the aggregate market liquidity series and Panel B reports these values for the series obtained by calculating the spread between monthly HY and IG liquidity series. $S_i, i = 1, \ldots, 4$, show different regimes and $P(S_t = i | S_{t-1} = i)$ is the persistence of each regime. The liquidity and trading activity variables have similar definitions as described in the text and the previous tables.

Panel A: Aggregate market monthly time series

	Model parameters							Percentage of Sub-periods			
	α_{s_i}	ϕ_{1s_i}	ϕ_{2s_i}	δ_{s_i}	mean	std	persistence	Pre-crisis	Crisis	Post-crisis	Reg.
Amihud	0.08***	0.75***	-	0.02	0.30	0.03	0.97	0%	0%	0%	96%
	0.12***	0.75***	-	0.03	0.46	0.04	0.88	91%	26%	92%	4%
	0.21***	0.75***	-	0.03	0.81	0.05	0.00	6%	16%	8%	0%
	0.26***	0.75***	-	0.14	1.02	0.20	0.90	3%	58%	0%	0%
Model: AR(1) with 4 regimes and constant ϕ coefficients AIC: -535.01 BIC: -495.17											
RTC	0.00	0.94***	-	0.01	0.00	0.03	0.04	31%	0%	31%	48%
	0.03**	0.94***	-	0.03	0.50	0.09	0.32	5%	53%	11%	0%
	0.03***	0.94***	-	0.02	0.50	0.06	0.48	62%	11%	53%	56%
	0.10***	0.94***	-	0.02	1.67	0.06	0.00	3%	37%	6%	0%
Model: AR(1) with 4 regimes and constant ϕ coefficients AIC: -632.33 BIC: -592.50											
HW	0.07***	0.55***	0.34***	0.05	0.64	0.10	0.97	92%	16%	81%	100%
	0.25***	0.55***	0.34***	0.21	2.27	0.40	0.87	8%	84%	19%	0%
Model: AR(2) with 2 regimes and constant ϕ coefficients AIC: -349.17 BIC:-317.35											
RPT	0.01	0.55***	0.41***	0.03	0.25	0.09	0.95	98%	68%	97%	100%
	0.07***	1.16***	-0.21***	0.01	1.40	0.04	0.31	2%	32%	3%	0%
Model: AR(2) with 2 regimes and switching ϕ coefficients AIC: -618.19 BIC: -570.47											
Trades	3.38***	0.58***	0.25***	2.07	19.88	3.37	0.99	98%	0%	0%	12%
	9.27***	0.58***	0.25***	5.99	54.53	9.76	0.99	2%	100%	100%	88%
Model: AR(2) with 2 regimes and constant ϕ coefficients AIC: 810.14 BIC: 841.95											
Volume	2.54***	0.53***	0.17**	1.32	8.41	1.74	0.59	80%	42%	28%	48%
	2.33	0.54***	0.44***	3.29	99.50	13.83	0.63	20%	58%	72%	52%
Model: AR(2) with 2 regimes and switching ϕ coefficients AIC: 742.24 BIC:789.96											
Zero	2.75**	0.96***	-	0.92	68.75	3.29	0.98	51%	84%	100%	100%
	94.27***	-0.23	-	2.22	76.64	2.28	0.96	49%	16%	0%	0%
Model: AR(1) with 2 regimes and switching ϕ coefficients AIC: 481.23 BIC:513.10											
%RPT	-0.03	0.67***	0.31***	1.83	-1.50	8.05	0.80	0%	0%	0%	20%
	0.33	0.67***	0.31***	0.90	16.50	3.96	0.99	100%	100%	100%	80%
Model: AR(2) with 2 regimes and constant ϕ coefficients AIC: 407.89 BIC: 439.71											
%Interdealer	30.6***	-	-	6.84	30.6	6.84	0.99	100%	95%	0%	0%
	46.6***	-	-	1.94	46.6	1.94	0.99	0%	5%	100%	100%
Model: Intercept model with two regimes AIC: 825.4923 BIC: 841.454											
% Block Vol.	6.61	-	-	1.03	6.61	1.03	0.99	100%	100%	3%	0%
	8.41	-	-	1.18	8.41	1.18	0.98	0%	0%	97%	100%
Model: Intercept model with two regimes AIC: 465.42 BIC: 481.38											

Panel B: IG-HY monthly time series

	Model parameters							Percentage of Sub-periods			
	α_{s_i}	ϕ_{1s_i}	ϕ_{2s_i}	δ_{s_i}	mean	std	persistence	Pre-crisis	Crisis	Post-crisis	Reg.
Amihud	0.09***	0.37***	-	0.06	0.14	0.00	0.98	82%	5%	86%	100%
	0.33***	0.09	-	0.15	0.36	0.02	0.96	18%	95%	14%	0%
Model: AR(1) with 2 regimes and switching ϕ coefficients AIC: -310.97 BIC: -279.105											
RTC	-0.05**	0.59***	0.37***	0.08	-1.25	0.06	0.64	26%	42%	8%	24%
	-0.002	0.59***	0.37***	0.04	-0.05	0.02	0.76	49%	47%	67%	56%
	0.09***	0.59***	0.37***	0.05	2.25	0.02	0.00	25%	11%	25%	20%
Model: AR(2) with 3 regimes and constant ϕ coefficients AIC: -335.78 BIC: -296.014											
HW	-0.62	-	-	0.43	-0.62	0.43	0.94	0%	63%	17%	0%
	0.25	-	-	0.11	0.25	0.11	0.91	40%	11%	42%	0%
	0.49	-	-	0.13	0.49	0.13	0.97	60%	26%	42%	100%
Model: Intercept model with 3 regimes AIC: -105.57 BIC:-81.63											
RPT	-0.03***	0.55***	0.33***	0.05	-0.25	0.01	0.64	74%	95%	83%	64%
	0.06	0.55***	0.33***	0.09	0.50	0.03	0.35	26%	5%	17%	36%
Model: AR(2) with 2 regimes and constant ϕ coefficients AIC: -326.73 BIC: -294.91											
Trades	-0.67	0.69***	0.19**	3.08	-5.58	35.87	0.97	86%	37%	3%	12%
	-0.51	0.69***	0.19**	11.79	-4.25	525.6	0.97	14%	63%	97%	88%
Model: AR(2) with 2 regimes and constant ϕ coefficients AIC: 986.40 BIC: 1018.21											
Volume	-0.87	0.80***	-	5.86	-4.34	95.25	0.87	51%	47%	83%	56%
	-0.15	0.80***	-	2.81	-0.75	21.95	0.81	49%	53%	17%	44%
Model: AR(1) with 2 regimes and constant ϕ coefficients AIC: 877.75 BIC: 901.66											
Zero	0.12	0.85***	-	1.12	0.80	4.52	0.74	78%	47%	86%	76%
	0.18	0.85***	-	1.78	1.20	11.42	0.68	22%	53%	14%	24%
Model: AR(1) with 2 regimes and constant ϕ coefficients AIC: 528.96 BIC: 552.87											
%RPT	7.69	-	-	2.39	7.69	2.39	0.99	0%	47%	100%	100%
	18.49	-	-	1.59	18.49	1.59	0.98	100%	52%	0%	0%
Model: Intercept model with 2 regimes AIC: 645.82 BIC: 661.78											
%Interdealer	-1.63	-	-	2.3	-1.63	2.3	0.98	63%	100%	22%	0%
	3.73	-	-	2.6	3.73	2.6	0.99	37%	0%	78%	100%
Model: Intercept model with 2 regimes AIC: 698.55 BIC: 714.51											
% Block Vol.	-2.01	-	-	2.08	-2.01	2.08	0.99	98%	53%	42%	100%
	2.14	-	-	3.61	2.14	3.61	0.96	2%	47%	58%	0%
Model: Intercept model with 2 regimes AIC: 686.99 BIC: 702.96											

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Impact of Rating Change Events on Corporate Bond Trading Costs and Liquidity

By

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ABSTRACT

This paper studies the impact of credit rating changes on corporate bonds transaction costs, and the determinants of abnormal illiquidity during short windows around the rating announcements in normal versus distressed market conditions. Our findings suggest decreased (increased) liquidity around downgrades (upgrades) announcements, with relatively stronger effects around downgrades. Higher levels of cumulative abnormal illiquidity (CAIL) are observed over the ten days window following the event for fallen angel and multi-level downgrades. Downgrades exhibit stronger negative effect on the Amihud price impact measure for bonds during the financial crisis, but there is no evidence of similar crisis effect for bid-ask spreads. Finally, trading activity as well as bond and issuer characteristics affect CAIL around the rating events.

1. Introduction

Credit rating agencies play a substantial role in financial markets by providing opinions about the creditworthiness of bond issuers as well as the default risk of particular issues. Several bond market regulations designed to restrict risk taking by financial institutions are based on credit ratings. Campbell and Taksler (2003) highlight that institutions subject to rating based restrictions on their holdings own more than half of all corporate bonds. Therefore a change in credit rating of a bond from one scale to another has relevant implications for most bondholders and potential buyers in terms of their portfolio allocation decisions and capital requirements. In particular, downgrades that move the bonds out of the investment grade category can elicit selling pressure or even fire sale of the fallen angels by at least a segment of the market as demonstrated by Ellul, et al. (2011).

While the information content of credit rating announcements and the impact of rating changes on stock and bond prices have been the subject of several studies (e.g. Hand et al., 1992; Kliger and Sarig, 2000; May, 2010 among others), the impact of rating changes on corporate bonds liquidity and trading activity is not well understood. Kim and Verrecchia (1994) predict that stock liquidity deteriorates around the time new information is released to the market and returns to normal afterwards. The price pressure typically do not last for more than a few days in the equity market, but the impact of rating changes on corporate bonds liquidity are likely to be larger and more persistent.

This paper explores the impact of credit rating changes on corporate bonds liquidity around the announcement date. We follow an event study approach appropriate for corporate bond market in the spirit of Bessembinder et al. (2009), May (2010) and Ellul et al. (2011) to measure abnormal (il)liquidity around the rating events.

Previous research in this area is mainly focused on price pressure and trading activity around the fallen angel downgrades. For example Ellul et al. (2011) investigates fire sales of downgraded corporate bonds induced by regulatory constraints imposed on insurance companies. They find that insurance companies that are relatively more constrained by regulations are more likely to sell downgraded bonds. Moreover, they find that while many bonds do not exhibit a strong price response to the downgrade, in general those bonds subject to a high probability of regulatory induced selling show significant price declines and subsequent reversals. The price effects appear larger during periods in which insurance companies as a group are relatively more distressed and when other potential buyers' capital is relatively scarce.

Ambrose, Cai and Helwege (2012) also examine the trading activity when investment grade bonds are downgraded to junk status. Based on a sample of insurance companies, Ambrose, Cai and Helwege (2012) suggest that while insurance companies are more active in selling fallen angels following downgrades, these increased sales only account for a small portion of their overall fallen angel holdings. They argue that it is unlikely that any regulations or internal policies require these institutions to sell their holdings of fallen angels immediately after downgrade, as selling at fire sale price may have more adverse consequences for the firm.

In case of a bankruptcy or default event, Jankowitsch et al. (2014) document temporary high trading activity and price pressure on the default event day itself exclusively. Wang and Han (2015) also find an increase in abnormal bid-ask spreads around default.

Unlike many previous studies, we do not restrict our analyses to fallen angels downgrades. Instead, we study the impact of downgrades and upgrades across all ratings but allow for possible non-linear liquidity effect of rating changes within investment grade vs. high yield range as well as the asymmetric effect of downgrades vs. upgrades. We then study the cross sectional determinants of abnormal illiquidity around credit rating changes. Our relatively long sample period allows the examination of effects in both normal economic conditions as well as the crisis period.

Overall, the results suggest asymmetric findings: While downgrades significantly affect the bond liquidity around announcement date for all measures of liquidity, significant results for upgrades are only found for the Amihud measure but not for bid-ask spread measures. Examining mean and median cumulative abnormal illiquidity (CAIL) over several windows around the rating announcement date shows a positive and significant abnormal illiquidity associated with credit rating downgrades and negative abnormal illiquidity around upgrades.[17] Consistent with the previous literature on the impact of rating changes on stock and bond returns, we find asymmetric impact for upgrades vs. downgrades on trading costs where the effect of upgrades is much smaller than the effect of downgrades (Holthausen and Leftwich,

[17]While Kim and Verrecchia (1994) suggests that liquidity deteriorates around the time new information is released to the market and returns to normal a few days afterwards, the impact of rating changes on corporate bonds liquidity are likely to be larger and more persistent, so we use a variety of longer windows in our study.

1986; Hand et. al. 1992). Holthausen and Leftwich (1986) argue that rating agencies allocate more resources to revealing negative credit information than positive information because the loss of reputation is more severe when a false rating is too high than when it is too low. As a result downgrades represent information not yet known by the market, whereas upgrades confirm information that is already available. Moreover, the downgrades may trigger forced selling or fire sales whereas the upgrades are not followed by forced buying. These heterogeneous trading patterns around downgrades and upgrades may cause different behavior of liquidity proxies in terms of their magnitude around downgrades and upgrades.

Interestingly, the mean CAIL is positive and significant prior to the downgrade announcement date, which suggests that downgrade events are at least partially anticipated by the market. This result, which is consistent with the previous literature, may either be due to advance notice of potential downgrades by inclusion in the watch list of credit rating agencies well before the actual downgrade date or a result of delayed rating changes by credit rating agencies based on their through-the-cycle approach, as in Altman and Rijken (2006).

The results also suggest a heterogeneous effect of rating changes across the investment grade and high yield boundary. Downgrades from investment grade to high yield have stronger and more persistent adverse impact on abnormal illiquidity both in terms of price impact and bid-ask spreads, whereas upgrades to investment grade have more muted and transitory impact. Downgrades to high yield category may impose a selling pressure on financial institutions such as insurance companies and pension funds, while providing an opportunity for less restricted investors such as hedge funds and high yield mutual funds to buy these securities at deep discounts (Fridson and Cherry, 1992, Fridson and Sterling, 2006 and Dor and Xu, 2011). The selling pressure accompanied by the "slow moving capital" coming to the market by these new investors leads to a shallow market for fallen angels around the downgrade event. We also find that the positive impact of downgrades on abnormal illiquidity is more pronounced for downgrades within the investment grade category compared to the downgrades within the high yield category.

Analyzing the rating changes in normal versus crisis period shows that while the negative impact of downgrades is stronger during the financial crisis, no significant impact for upgrades are observed during this period; however, since the number of upgrades during the crisis is much lower compared to normal times, this result should be interpreted with caution.

The cross sectional determinants of abnormal illiquidity suggest that the adverse effect of downgrades on bond liquidity is more severe for downgrades of more than one step, and downgrades that simultaneously affect several bonds of the same firm. Bonds with larger issue size experience significantly better liquidity around rating events. Sectors matter: bonds issued by financial and utility firms experience worse liquidity conditions in the event of a downgrade. The selling pressure around rating change events exacerbates the adverse impact of downgrades on liquidity , and higher trading volume around both downgrades and upgrades significantly improves the liquidity as defined by market depth and bid-ask spreads.

The rest of the paper is organized as follows: Section 2 describes the sample of rating changes and summary statistics, Section 3 describes the liquidity measures used in this study, Section 4 describes the event study methodology, Section 5 explains and discusses the event study results, Section 6 examines the cross sectional determinants of abnormal (il)liquidity around the rating events and section 7 concludes.

2. Sample of rating changes

To construct the event study sample, we use FISD to identify rating changes by Moody's, S&P and Fitch from July 2002 to September 2014. We exclude bonds that are denominated in a currency other than US dollar or have a foreign issuer, variable rate and zero coupon bonds, bonds that have credit enhancement, convertibles, asset-backed, callable, putable, exchangeable, fungible, preferred, tendered, and bonds that are part of a unit deal are excluded from the sample. Following May (2010), we also require bond's maturity date to be at least one year from its rating change date. In the event of multiple rating changes within five days interval, only the earliest rating change is included. If bonds of the same firm are downgraded (upgraded) on same day by more than one rating agency, only one agency's rating change is included according to the following priority: Moody's, S&P and Fitch. We also exclude the downgrades where the new rating is below Caa/CCC. Since these downgrades are very likely to be concurrent with the firm's default, there are more likely to be associated with other simultaneous events and information as pointed out by May (2010). We also exclude the upgrades where the old rating is below Caa/CCC to have symmetric downgrades and upgrades samples. Applying these filters result in a sample of 7,903 bond rating changes (5,373 downgrades and 2,530 upgrades). At the firm level, these represent 4,043 rating change events (2,613 downgrades and 1,430 upgrades).

To keep bonds with the sufficient number of trades in the event study sample, we require that bonds trade on at least 10 days during the entire sample period and also similar in spirit to Ellul et al. (2011)'s procedure, we require that bonds trade on at least 1 day before Day -20, one day between Days -20 to 0, one day between Days 0 and $+20$, and one day after Day $+20$ from the event. After imposing these restrictions, the final sample consists of 5,137 observations at the issue level (3,581 downgrades and 1,556 upgrades). Among these observations, 627 bonds trade on less than 10 days during the $[-20,+20]$ window. 363 bonds trade on less than 5 days during the $[-20,+20]$ window and 25 bonds are traded only once during the same window. At firm level, the final sample includes 2780 unique rating change events (1855 downgrades and 925 upgrades).

Table 8 shows the bond level distribution of rating changes by rating agency and different rating change characteristics. There are a total of 3,581 downgrades and 1,556 upgrades in our sample. Panel A shows the distribution of rating changes by calendar year. The number of downgrades in 2004 to 2007 is generally less than in 2002 or 2003. Downgrades are particularly rare during 2007 right before the financial crisis. The number of downgrades surges during crisis period of 2008 and 2009, but then resumes to a level as small as, or smaller than before the crisis. The 1,184 downgrades that exist in our sample during 2008-2009 constitute 33% of all sample downgrades. The highest number of upgrades observed in a single year is 266 which belong to 2007 after which the number of upgrades decreases sharply during the crisis period. Higher number of upgrades is observed in the years following the financial crisis. The smaller number of Fitch rating changes compared to the other agencies is due to lower market share of Fitch.

Panel B shows the distribution by size of the rating change. Almost all downgrades (72%) and upgrades (82%) in the sample are just by one grade. Among the credit rating agencies, Fitch appears to have the highest percentage of downgrades and upgrades by more than two grades. 12.1% of Fitch downgrades are by three or more notches and 12.9% of its upgrades are by three or more notches. In general larger size of rating changes is slightly more common for downgrades than for upgrades.

Panel C of Table 8 shows the sample distribution by pre-downgrade and pre-upgrade letter rating class. Over a third of downgrades (38.4%) and upgrades (39.8%) in the sample are from A letter rating class. Panel D shows the number of rating changes across the investment grade boundary. In total, the sample includes 305 downgrades from investment grade to non-investment grade (8.5% of downgrades) and 123 upgrades from non-investment grade to investment grade (7.9% of upgrades) in the sample.

3. Liquidity measures

In this study, the illiquidity is proxied by Amihud (2002) measure and a roundtrip cost measure (RTC)[18]. The Amihud measure is from Amihud (2002). The daily Amihud measure is calculated as the average ratio of absolute return to the trade size of consecutive transactions during a day:

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[18] Hong and Warga (HW) measure is also examined, however since the results were qualitatively similar to that of RTC, we haven't reported them for brevity.

$$Amihud_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \frac{\left| \frac{P_{i,j} - P_{i,j-1}}{P_{i,j-1}} \right|}{Q_{i,j}} \qquad (1)$$

where $N_{i,t}$ is the number of trades of bond i on day t, $P_{i,j}$ and $P_{i,j-1}$ are the prices for two consecutive trades (j - 1th and jth), for bond i on day t. $Q_{i,j}$ is the size of the jth trade for bond i. At least two transactions are required on a given day to calculate the measure. A larger Amihud measure indicates higher price impact in response to a given volume of trading and reflects higher illiquidity.

Roundtrip cost (RTC): We develop a roundtrip cost measure in the spirit of Feldhütter (2012). Feldhütter defines bond trades to be part of an imputed roundtrip transaction (IRT) if two or three trades for a given volume occur within fifteen minutes. Because the buy/sell indicator is not available in the TRACE data for the majority of his study period, he assumes the highest price to be an investor buying from a dealer, the lowest price to be an investor selling to a dealer and the investor roundtrip cost to be the highest minus the lowest price. We modify this measure using buy/sell indicators in the following way: First, we identify multiple transactions for the same bond on the same day and same volume. Based on this definition 1,897,735 IRTs exist in our sample. 5,518,173, transactions out of 7,988,736 are part of an IRT that form around 69% of total observations. These transaction groups are either B/S: include at least a customer buy and a customer sell transaction, D/B: Include only customer buy and interdealer transactions, S/D: include only customer sell and interdealer transactions, B: Include only customer buy transactions, S: Include only customer sell transactions, D: Include only interdealer transactions. Next, we calculate roundtrip cost using the first three types in the following way:

$$RTC = \begin{cases} \overline{p_t^{buy}} - \overline{p_t^{sell}} & \text{If transaction group is } S/B \\ \overline{p_t^{buy}} - \overline{p_t^{dealer}} & \text{If transaction group is } D/B \\ \overline{p_t^{dealer}} - \overline{p_t^{sell}} & \text{If transaction group is } S/D \end{cases} \qquad (2)$$

Where $\overline{P_t^{buy}}$ is the mean customer buy price (Ask) and bid $\overline{P_t^{sell}}$ is the mean customer sell price and $\overline{P_t^{Dealer}}$ is the mean interdealer price. Finally the daily roundtrip cost for each bond is calculated as the average of all roundtrip costs for that bond during that day.

We examine the distribution of IRTs across various trade sizes to test the representativeness of the measure for the entire sample and identify the potential biases. Panel A of Table 9 shows the distribution of all transactions as well as transactions that are part of an IRT across different size groups. As we can see, more than 78% of all transactions in our sample are retail sized trades defined as trades below $100,000. Around 74% of retail sized transactions and around 51% of institutional sized trades are part of an IRT. Only 47% of trades above $1,000,000 are part of an IRT. These percentages imply that retail sized trades are more likely to be part of an IRT which may cause an upward bias in our measure of bid-ask spreads. Panel B of Table 9 shows the distribution of various types of transaction groups across trading size groups. We can see that among all size groups D/B trades have a higher percentage compared to other types of trades.

4. Methodology

The event study methodology used in this study is similar in spirit to the procedures used by Bessembinder et al. (2009), May (2010) and Ellul et al. (2011). We use a matching portfolio model to calculate the abnormal bond illiquidity around rating changes. In order to control for market fluctuations in computing abnormal bond illiquidity, we use issues available in Enhanced TRACE data to construct illiquidity indices for each rating class that contain sufficient number of observations with non-missing illiquidity proxies.

The median numbers of bonds per issuer in our sample is 1. However around 43% of firms have more than one bond present in the sample with the maximum number being 26 bonds issued by General Electric Capital. This suggests a skewed distribution with a large number of firms having only one bond outstanding in the rating change sample, and a small number of firms with much more issues outstanding. This would cause the firms with larger number of bonds outstanding being over represented (Bessembinder et al., 2009). Moreover, usually several bonds of the same firm are downgraded on the same calendar date resulting in a clustered data with overlapping event windows. This clustering biases the standard errors downward because of the likely high correlation among bonds from the same firm, violating the assumption of independent observations and leading to inflated t-statistic (See Bernard 1987, Eberhart and Siddique, 2002 among others). To address these issues, we compute firm level abnormal illiquidity and treat each firm level rating change as a single observation. We compute the daily abnormal bond illiquidity as the raw illiquidity minus the contemporaneous illiquidity on an index of matched corporate bonds:

$$AB-ILLIQ_t = ILLIQ_t - I\_ILLIQ_t \qquad (3)$$

Where on day t, AB_ILLIQ_t is the abnormal bond illiquidity, $ILLIQ_t$ is the bond illiquidity and I_ILLIQ_t is the illiquidity of a value-weighted index of matched corporate bonds that did not experience a rating change in the period between Day $t-60$ to Day $t+60$.

The Enhanced TRACE is used to construct the matched corporate bond indices. We use Dick-Nielsen (2014) procedure to clean the Enhanced TRACE data and eliminate same day corrections and cancellations, reversals, agency transactions where the principal transaction has the same price as the agency transaction and one of the reports in each interdealer transaction pair. We also exclude special transactions such as trades which are not secondary market, trades under special circumstances, commissioned transactions, odd number of days to settlement, automatic give up trades, non-cash sales. Furthermore, following Edwards, Harris and Piwowar (2007) approach, we apply 20% median and 50% return reversal filter to eliminate outliers. The final Enhanced TRACE sample consists of 86,450,187 observations for 87,159 bonds.

The matching criteria is based on seven letter classifications using Moody's ratings and if unrated by Moody's, S&P rating of matched corporate bonds. These classifications include Aaa/AAA, Aa/AA, A, Baa/BBB, Ba/BB, B and Caa/CCC. To control for market-wide changes of the term structure, we divide the rating classes except Aaa and Caa into two maturity groups with the cutoff maturity being 4 years. Aaa/AAA and Caa/CCC classes are not divided by maturity due to much smaller number of traded bonds in these classes. The cutoff threshold is chosen in a way that, within a letter rating class, there is approximately the same number of matched bonds in each group.

For each of the twelve bond indices, we compute the daily illiquidity for each day in the sample period as the mean of daily illiquidity across all bonds in the index that are traded in that day. To be included in a given index on each day, the bond should be traded on that day. For firms with more than one bond downgraded/upgraded on the same date, we aggregate abnormal bond illiquidity by firm and consider each firm level rating change as a single observation. Abnormal illiquidity for firm j on day t is computed as:

$$AB\_ILLIQ_{j,t} = \frac{1}{N}\sum_{i=1}^{N} AB\_ILLIQ_{i,t} \qquad (4)$$

Where N is the number of bond issues in the sample for firm j. For a multiple day window, cumulative abnormal illiquidity (CAILs) is computed as the sum of the firm's daily abnormal bond illiquidity over the window.

5. Event study results

In this section, we test the impact of credit rating changes on corporate bonds illiquidity over several windows around the announcement date. The illiquidity is proxied by a price impact measure (Amihud) and a bid-ask spread measure (RTC). We study the impact over two pre-event windows and three post event windows: $[-20,-11]$, $[-10,-1]$, $[0,+1]$, $[0,+10]$ and $[+11,+20]$.

Panel A of Table 10 shows the impact of downgrades using the entire sample. We compute both mean cumulative abnormal illiquidity (mean CAIL) and median cumulative abnormal illiquidity (median CAIL) for the events windows. The number of observations used to calculate mean and median CAIL for each window is also reported. To test the statistical significance, we use t-test and signed-rank test for mean CAIL and sign test for median CAIL.

The results in Table 10 show that the mean CAIL is positive and significant prior to the downgrade date for both Amihud and RTC measures which implies that the rating change is anticipated by the market. Some previous studies have shown that credit rating agencies are relatively delayed in their rating decisions and a number of explanations have been provided by the literature for this phenomenon, including the rating stability hypothesis, reputation hypothesis and through-the-cycle as opposed to point-in-time approach of the credit rating agencies (Cantor (2001), Löffler(2005) and Altman and Rijken (2006)). However the magnitudes of mean and median CAIL are greater for the windows following the downgrade. These results indicate that there is a significant increase in the abnormal illiquidity associated with credit rating downgrade.

Next, we investigate whether there is a heterogeneous effect of rating changes within investment grade (IG) as opposed to rating changes within high yield (HY) category. Panel B of Table 10 reports the impact of downgrades within the investment grade category and Panel C shows the impact of downgrades within high yield range. Interestingly, the mean and median CAIL over all event windows are larger for IG downgrades vs. HY downgrades both for Amihud and RTC measures. The impact of HY downgrades on bonds' liquidity over most event windows, are insignificant. In general the mean and median cumulative abnormal illiquidity are positive but mostly insignificant around the rating event when a non-investment grade bond is further downgraded. Particularly the mean and median CAIL over $[+11, +20]$ window for HY downgrades are small (even slightly negative for RTC measure) which may imply that the impact is more transitory for the downgrades within the non-investment grade range.

These results may imply that downgrades of investment grade bonds are more consequential for the institutional investors holding them, as the downgrades may cause their portfolios to violate certain risk limits imposed by regulations or they may be indicative of the possibility that the bond will be soon downgraded to junk status. While the investors in high yield bonds such as high yield mutual funds and hedge funds may not share similar concerns. However since the number of observations are also much lower for downgrades within high yield range, we should take caution when interpreting these results.

Panel D of Table 10 shows the impact of downgrades that moves the firm out of (in to) the investment grade category. Both mean and median CAIL for fallen angel downgrades are positive and larger compared to either IG or HY downgrades. This evidence strongly highlights the role of regulations that prohibit financial institutions from holding non-investment grade bonds. These regulatory constraints may lead to forced selling of fallen angels by at least a segment of the market as demonstrated by Ellul, et al. (2011), and at the same time prevent other institutional investors from buying these bonds.

This situation also provides an opportunity for hedge funds and high yield mutual funds to buy the downgraded bonds at prices significantly below fundamental values (Fridson and Sterling, 2006). The selling pressure accompanied by the "slow moving capital" coming to the market by these new investors leads to a shallow market for fallen angels around the downgrade event.[19] Ellul et al. (2011) found that insurance companies that are relatively more constrained by regulations are more likely to sell downgraded bonds and those bonds subject to a high probability of regulatory induced selling show significant price declines and subsequent reversals, particularly when insurance companies as a group are relatively more distressed and when other potential buyers' capital is relatively scarce.

Table 11 examines the effect of upgrades announcements on bonds' liquidity. The results from Panel A generally show negative mean and median CAIL around upgrades for both Amihud and RTC measures. However the results for RTC measures are mostly insignificants except for the $[+11, +20]$ window. The magnitude of impact is also much smaller compared to the impact of downgrades for both Amihud and RTC measures.

In general, the results for upgrades are much smaller and less significant than those for downgrades. These results are in line with asymmetric market impact of downgrades and upgrades found in some prior studies (for example Holthausen and Leftwich (1986) and Hand, Holthausen and Leftwich (1992)). Similar to downgrade events, Panel B and C of Table 11 show that the impact of IG upgrades on bond liquidity is generally larger and more significant compared to that of HY upgrades except for $[+11, +20]$ window. Panel D of Table 11 shows that when the firm is upgraded from non-investment grade to investment grade we observe a negative abnormal illiquidity round the announcement date. For Amihud measure the impact is

[19] See Duffie (2010) for more explanation regarding slow moving capital hypothesis.

only significant for post-event windows of $[0,+1]$, $[0,+5]$ and $[0,+10]$.However, for the RTC measure the impact is not significant for any of the windows.

Panel A of Figure 6 compares the impact of IG downgrades, HY downgrades and fallen angel downgrades over $[-20,+20]$ days around the downgrade announcement date. This graph clearly demonstrates that fallen angel downgrades have more adverse impact on bond liquidity around the event compared to downgrades within either investment grade or high yield categories, emphasizing the role of restrictive regulations for holding high yield bonds by institutional investors. Panel B of Figure 6 shows similar results for upgrade events. In general the impact of upgrades on liquidity is much smaller; however the upgrades that move the bond from HY to IG category appear to have slightly larger impact.

Next, we study how the impact of rating changes on corporate bonds liquidity varies during normal economic conditions as opposed to crisis period. We split the sample to two subsample based on the economic conditions: Normal and Crisis. The Normal subsample covers the time period from the beginning of the sample (July 2002) to November 2007 and from July 2009 to September 2014. The crisis subsample starts from December 2007 and ends in June 2009. Table 12 shows the results of these analyses. Panel A shows the impact of downgrades during the normal economy and Panel B shows the impact of downgrades during the crisis period. Interestingly, we observe that the two liquidity measures seem to behave differently during normal vs. crisis period: For Amihud measure both mean and median CAIL around downgrades are larger for the crisis period over all studied event windows, indicating that downgrades have severe adverse impact on market depth for downgraded bonds during the crisis period. On the other hand, for bid-ask spread as measured by RTC, although the mean CAIL is still significant over all windows during the crisis period, the magnitude of impact appears to be smaller, compared to the normal period, for all event windows.

Panel C and D of Table 12 show the mean and median CAIL for upgrades in normal and crisis period. Interestingly, while we observe a negative and significant impact around upgrades during the normal economy, the significance disappears for the crisis period sample. In other words during the financial crisis upgrades didn't help improving liquidity of upgraded bonds around announcement date. However since the number of upgrades during the crisis period is very small, we should take caution in interpreting the latter results. Generally the impact of upgrades reported in Panel C and D are less significant for RTC measure compared to Amihud measure. Figure 7 also shows the cumulative abnormal illiquidity (CAIL) using Amihud as illiquidity proxy, during [-20, +20] days around the rating change announcements, confirming the results obtained in Table 12.

We also examine the number of trades and volume. Figure 8 shows the trading activity over [-20, +20] days around downgrades and upgrades. First we can observe that the average number of trades per day is higher around downgrade announcements compared to upgrade announcements for all types of trade (buy, sell and interdealer). Second, we can see that generally the number of trades doesn't appear to change much on the event date compared to the days prior to announcement which may imply that the rating event is anticipated by the market prior to actual announcement. However the average daily number of sell trades seems to increase during the $[+1, +10]$

window from downgrade announcement showing that the downgrades impose a selling pressure on the market to some extent. However, there is no evidence of fire sales following downgrades. Ambrose, Cai and Helwege (2012) also find that while the insurance companies are more active in selling fallen angels following rating downgrade but these increased sales only accounts for a small portion of their overall holdings of fallen angels. We can also observe that the average trading volume per day increases around 5 days prior to the event and starts to decline gradually after 6 days from the announcement date. However, similar results are not observed around upgrade announcements.

6. Determinants of bond abnormal illiquidity around rating events

The analysis presented in this section, identifies the determinants of corporate bond's abnormal illiquidity around rating change events. The dependent variable in all regressions is mean CAIL over $[0, +10]$ window using Amihud (CAIL (Amihud)) and RTC (CAIL (RTC)) as illiquidity proxies.

Table 13 reports the results of these analyses for downgrade events. We use *Crisis* dummy as an independent variable to test whether the impact of rating events on market liquidity of affected bonds is different in normal versus crisis period. The results are very different among regressions with CAIL (Amihud) vs. CAIL (RTC) as dependent variables. In particular, our results show that the negative impact of downgrades on bond liquidity (positive impact of downgrades on CAIL (Amihud)) was stronger during the recent financial crisis. However, we observe no significant crisis effect when the RTC bid-ask spread measure is used as illiquidity measure. In other words, results imply that the abnormal bid-ask spreads around downgrades were not significantly affected during crisis period whereas abnormal price impact of trades around downgrades became significantly larger. These findings confirm the results obtained in Table 12.

We also define $CAIL\ (-20,-10) > 0$as a dummy variable equal to 1, if CAIL over $[-20,-10]$ window is positive and 0 otherwise, to control for bond abnormal iliquidity prior to the announcement date. The coefficients for this variable are highly significant indicating that bonds with positive CAIL prior to the event date have higher abnormal illiquidity over 10 days from the downgrade announcement. Table 13 also provides evidence that the size of downgrade affects the magnitude of CAIL around downgrade event. The effect is more significant for Amihud measure. Also consistent with our prior findings in Table 10, the adverse effect of downgrades on liquidity is more severe when they cross the investment grade boundary.

We further control for bond old rating prior to rating change, by including two dummy variables, namely: *Old rating: Baa* (1 if bonds old rating is in Baa/BBB rating class and 0 otherwise) and *Old rating: HY* (1 if bonds old rating is between Ba1/BB+, Caa3/CCC- and 0 otherwise). The benchmark group is Aaa/AAA, A3/A- ratings. Interestingly, the coefficients for *Old rating: HY* is negative and significant in most of the settings, indicating that the liquidity of high yield bonds that are further downgraded are less affected around the downgrade announcement date compared to the bonds that belong to the benchmark group. This finding is consistent with the previous results from Table 10. Furthermore, the results show that if more bonds of the same firm are simultaneously affected by the downgrade, the CAIL around downgrade event will be larger.

Next, we examine the effect of trading activity on abnormal illiquidity around rating events. The results from Table 13 show a positive and significant coefficient for *#customer sell* variable particularly for regressions with CAIL (Amihud) as dependent variable. This result implies that a selling pressure around the downgrade announcement date will push up the abnormal price impact of trades which is consistent with our expectations.[20] On the other hand, the results show that an increase in average trading volume leads to a significant decrease in abnormal transaction costs (bid-ask spread) around downgrades. We can also observe that bonds with larger issue size enjoy better liquidity both in terms of price impact and bid-ask spread around downgrade events. Also bonds with higher coupon rates and bonds that are issued by utility firms tend to have higher abnormal bid-ask spread around default.

Table 14 shows the determinants of cumulative abnormal illiquidity (CAIL) around upgrade events. For upgrades the coefficients of *crisis* variable is insignificant in all settings implying that the abnormal illiquidity around upgrade events are not significantly changed during the crisis period comparing to the normal economic conditions. Also the coefficients for $CAIL(-20,-10)<0$ dummy variable are negative and significant indicating that bonds with negative CAIL prior to the event date experience lower abnormal illiquidity over 10 days from the downgrade announcement. Upgrades that move the bond in to the investment grade category significantly decrease the abnormal Amihud around upgrade event. However they

[20] *#customer sell* is defined as is the average number of daily customer sells across all the bonds of the firm that are affected by the rating change over the [0,+10] days window around rating event.

have no significant impact on abnormal bid-ask spread around upgrade. The negative and significant coefficients of "*Old rating: HY"* in column 6 and 7 show that upgrades from high yield category are associated with lower abnormal transaction costs around the announcement. We can also observe that higher average trading volume is associated with lower abnormal illiquidity around upgrade events. The coefficients for bond and firm characteristics generally show similar signs as in Tanble9. In particular bonds with larger issue size enjoy better liquidity around upgrades and bonds with higher age experience lower liquidity (higher CAIL (Amihud)) during the ten days after the upgrade announcement.

7. Conclusion

This study examines the impact of rating changes on bond's liquidity around the announcement date. The results generally show positive and significant cumulative abnormal illiquidity (CAIL) around downgrades and negative CAIL around upgrades. Consistent with prior literature, we find smaller and less significant impact for upgrades. We also find that the negative impact of downgrades on liquidity is more severe for fallen angel downgrades. Moreover, our findings suggest larger impact for downgrades and upgrades within investment grade category compared to rating changes within the high yield range. Analyzing the trading activity around rating changes show that downgrades elicit more trades (buy, sell and interdealer) compared to upgrades. There is a modest evidence of selling pressure after the downgrade date and an increase in trading volume around the downgrade announcements.

We also study the determinants of abnormal illiquidity around the rating change announcement. The results show that downgrades that occurred during the financial crisis are associated with higher abnormal illiquidity in terms of price impact (as measured by Amihud) but not bid-ask spreads. Moreover, the results show that downgrades of larger size, fallen angel downgrades and downgrades that simultaneously affected several bonds of the same firm have more adverse impact on liquidity around announcement. Selling pressure around rating event exacerbates the negative impact of downgrade on liquidity, and higher trading volume around the event is associated with lower CAIL both around downgrades and upgrades. Bonds with larger issue size experience significantly better liquidity around rating events both in terms of price impact and bid-ask spreads and downgrades of financial and utility firms are associated with higher abnormal illiquidity.

References

Abad, Pilar, Antonio Diaz, Ana Escribanoand, and M. Dolores Robles, 2015, Credit rating announcements and bond liquidity, working paper, EFMA 2015 proceedings.

Altman, Edward I., and Herbert Rijken, 2006, The added value of rating outlooks and rating reviews to corporate bond ratings, Working Paper, New York University Salomon Center.

Ambrose, Brent W., Kelly N. Cai, and Jean Helwege, 2012, Fallen angels and price pressure, *Journal of Fixed Income* 21, 74–86.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Bernard, Victor L., 1987, Cross-sectional dependence and problems in inference in market-based accounting research, *Journal of Accounting Research*, 1-48.

Bessembinder, Hendrik , Kathleen M. Kahle, William F. Maxwell, and Danielle Xu, 2009, Measuring abnormal bond performance, *Review of Financial Studies* 22:4219–4258.

Campbell, John Y., and Glen B. Taksler, 2003, Equity volatility and corporate bond yields, *The Journal of Finance* 58, 2321-2350.

Cantor, Richard, 2001, Moody's investors service response to the consultative paper issued by the Basel Committee on Banking Supervision and its implications for the rating agency industry, *Journal of Banking and Finance* 25, 171–186.

Dick-Nielsen, Jens, 2014, How to clean enhanced TRACE data, Working paper, SSRN. http://ssrn.com/abstract=2337908.

Dor, Arik Ben, and Zhe Xu, 2011, Fallen angels: Characteristics, performance, and implications for investors, *The Journal of Fixed Income* 20, 33-58.

Duffie, Darrell, 2010, Presidential address: Asset price dynamics with slow-moving capital, *The Journal of Finance* 65:1237–67.

Eberhart, Allan, and Akhtar Siddique, 2002, The long-term performance of corporate bonds (and stocks) following seasoned equity offerings, *Review of Financial Studies* 15, 1385–1406.

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate bond market transaction costs and transparency. *Journal of Finance* 62, 1421–1451.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T. Lundblad, 2011, Regulatory pressure and fire sales in the corporate bond market, *Journal of Financial Economics* 101, 596–620.

Feldhütter, Peter, 2012, The same bond at different prices: identifying search frictions and selling pressures, *Review of Financial Studies* 25(4),1155–1206.

Fridson, Martin, and Karen Sterling, 2006, Fallen Angels: A Separate and Superior Asset Class, *Journal of Fixed Income* 16, 22-29.

Hand, John R. M., Robert W. Holthausen, and Richard W. Leftwich, 1992, The effect of bond rating agency announcements on bond and stock prices, *The Journal of Finance* 47, 733-752.

Holthausen, Robert W., and Richard W. Leftwich, 1986, The effect of bond rating changes on common stock prices, *Journal of Financial Economics* 17, 57-89.

Jankowitsch, Rainer, Florian Nagler, and Marti G. Subrahmanyam, 2014, The determinants of recovery rates in the U.S. corporate bond market, *Journal of Financial Economics*,114,155-177.

Kim, Oliver, and Robert E. Verrecchia, 1994, Market liquidity and volume around earnings announcements, *Journal of Accounting and Economics* 17, 41-67.

Kliger, Doron, and Oded Sarig, 2000, The Information Value of Bond Ratings, *Journal of Finance* 55:2879-2902.

Löffler, Gunter, 2005, Avoiding the rating bounce: why rating agencies are slow to react to new information, *Journal of Economic Behavior & Organization* 56, 365–381.

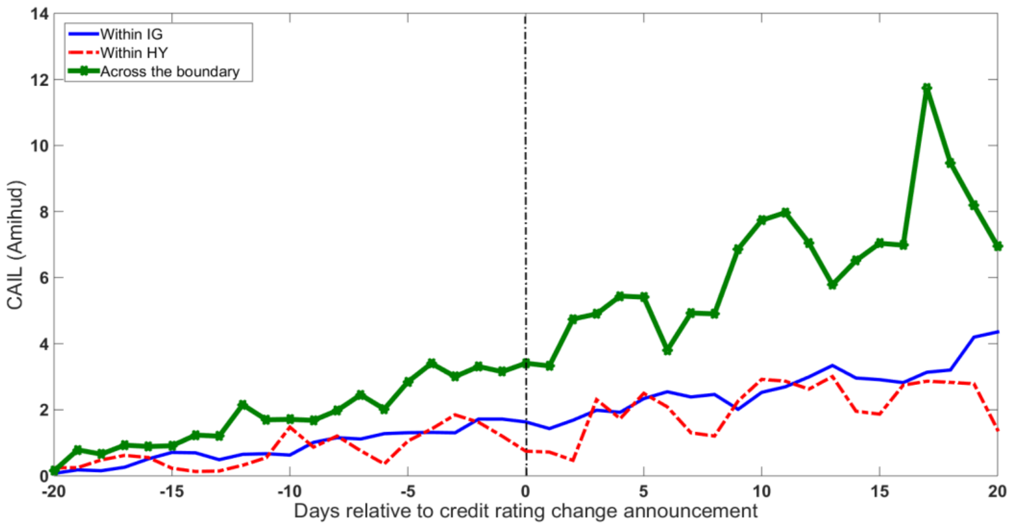
May, Anthony D., 2010, The impact of bond rating changes on corporate bond prices: new evidence from the over the-counter market, *Journal of Banking and Finance* 34:2822–2836.

Wang, Ke, and Song Han, 2015, Liquidity and price impacts of financial distress: Evidence from market for defaulted bonds, 2015 Financial Management Association Annual Meeting proceedings.

Figure6:

The impact of credit rating downgrades (Panel A) and upgrades (Panel B) within investment grade category/ within Non-investment grade category and across the investment grade boundary, on corporate bond market illiquidity during -20 Days to 20 Days from rating change.

Panel A: Downgrade



Panel B: Upgrade

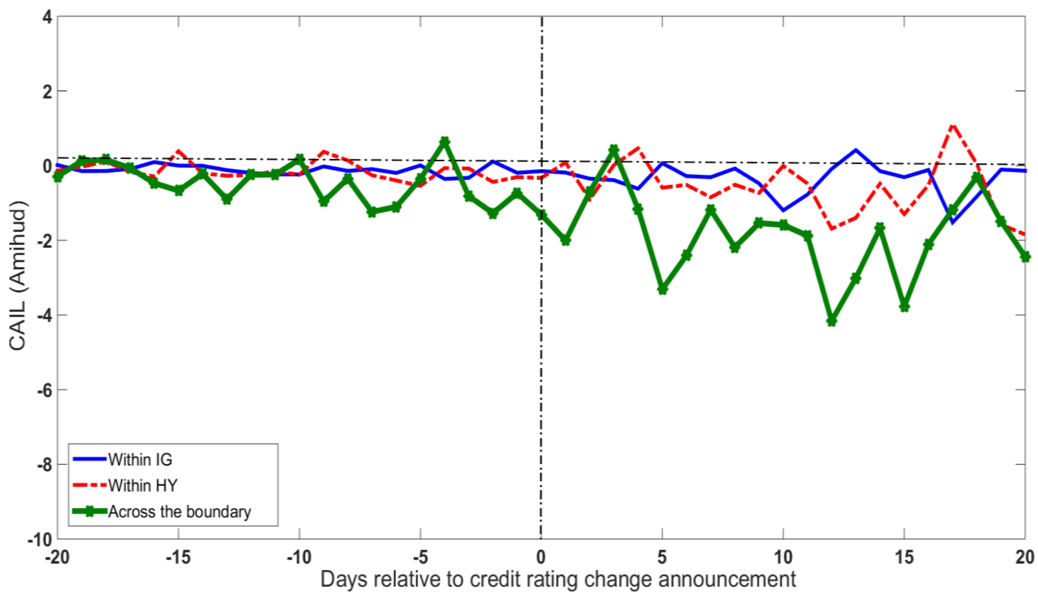
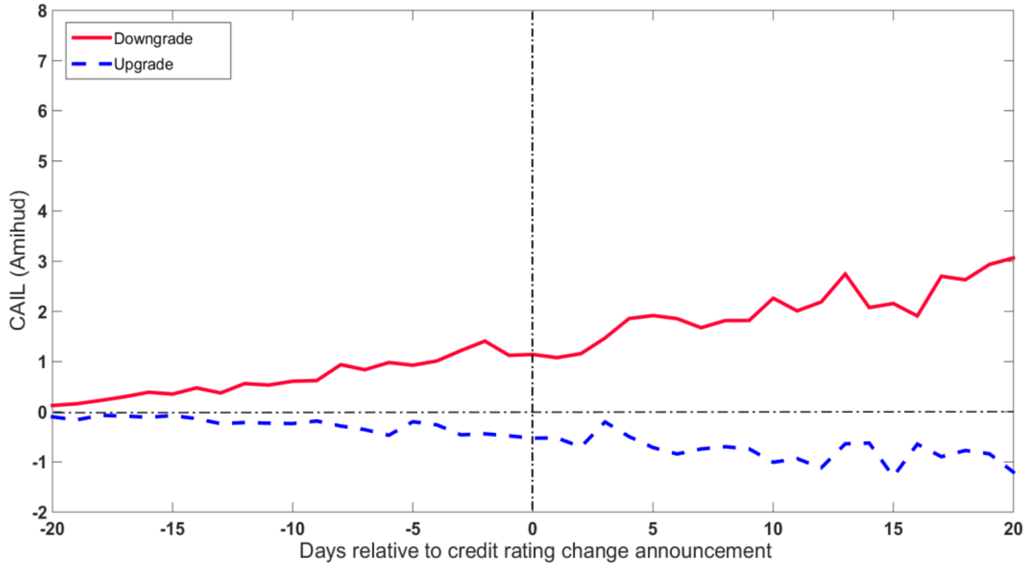


Figure 7: The impact of credit rating change announcements on corporate bond market illiquidity (Amihud) during -20 Days to 20 Days from rating change in normal versus crisis period. The crisis period starts from Dec.2007 and ends in June 2009.

Panel A: Normal period



Panel B: Recession period

Figure 8: Trading activity around credit rating downgrade/ upgrade events

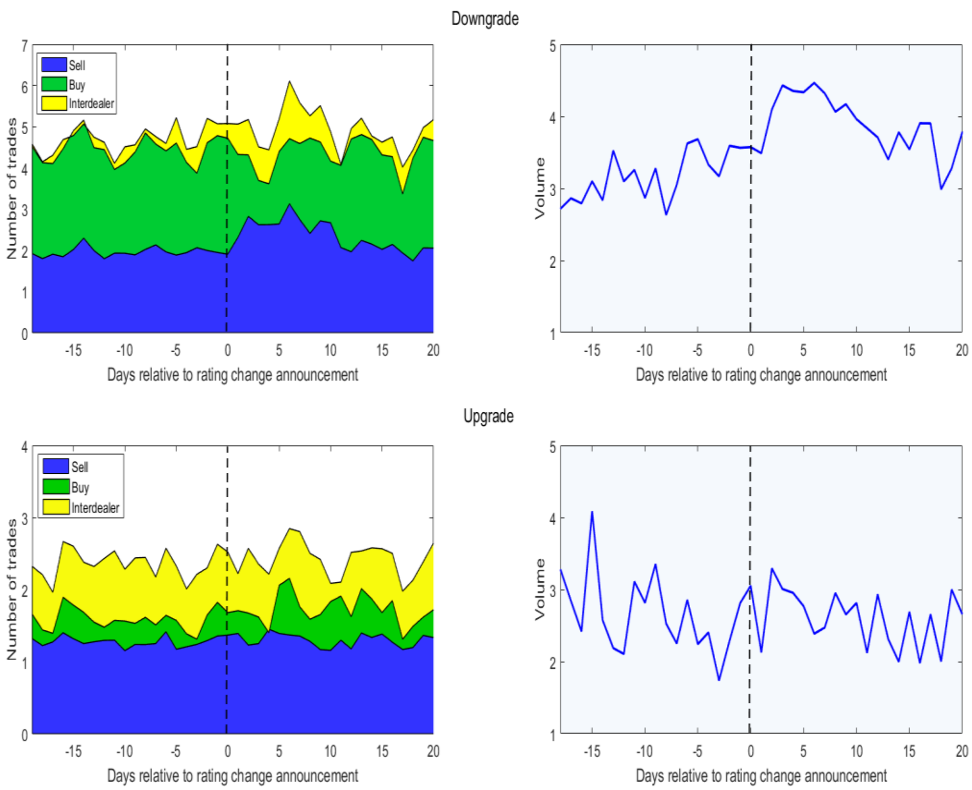


Table 8: Distribution of rating changes by rating agency and rating change characteristics. This table presents the bond level rating change distributions. Our event study sample consists of 3,581 downgrades and 1,556 upgrades by Moody's, S&P and Fitch during the period from July 2002 to September 2014. Panel A reports the rating change distribution by calendar year. Panel B reports the distribution by size of the rating change. Panel C reports the sample distribution by pre-downgrade (pre-upgrade) letter rating class. Panel D reports the number of downgrades (upgrades) that moved the bond out of (in to) the investment grade category.

	Downgrades				Upgrades			
	All	Moody's	S&P	Fitch	All	Moody's	S&P	Fitch
Panel A: Sample distribution by calendar year								
2002	450	156	198	96	46	31	11	4
2003	507	192	177	138	169	80	51	38
2004	215	83	72	60	164	70	49	45
2005	239	91	79	69	191	53	86	52
2006	226	103	72	51	227	68	110	49
2007	172	95	40	37	266	104	116	46
2008	599	245	184	170	73	17	32	24
2009	585	292	184	109	61	18	30	13
2010	139	51	59	29	94	32	27	35
2011	218	54	112	52	102	27	43	32
2012	206	131	30	45	106	46	36	24
2013	25	5	11	9	57	20	18	19
Total	3581	1498	1218	865	1556	566	609	381
Panel B: Sample distribution by size of the rating change								
1 grade	2576	1029	946	601	1279	457	533	289
2 grades	698	361	178	159	182	86	53	43
3 grades	161	52	48	61	37	6	11	20
4 grades	60	21	19	20	20	9	1	10
5 grades	40	23	13	4	20	5	4	11
6+ grades	46	12	14	20	18	3	7	8
Panel C: Sample distribution by pre-downgrade or pre-upgrade letter rating class								
Aaa, AAA	60	24	25	11	0	0	0	0
Aa, AA	803	369	217	217	120	71	40	9
A	1375	558	472	345	620	207	297	116
Baa, BBB	765	294	290	181	364	104	125	135
Ba, BB	350	141	134	75	247	88	79	80
B	197	94	73	30	156	67	61	28
Caa, CCC	31	18	7	6	49	29	7	13
Panel D: Number of rating changes that cross the investment grade boundary								
Across inv. grade	305	113	115	77	123	43	46	34

Table 9: Distribution of round-trip trades by trade size

This table presents the number and percentage of round-trip trades (IRTs) within each transaction size class. Panel B shows the distribution of trade types and their average round trip cost (RTC) across trading size groups.

Panel A: Number and percentage distribution of IRTs and IRT transactions across trade sizes

Trade size	Total	Column%	# IRT trades	Row%	#IRTs	Column%
Retail	6,276,041	78.6	4,651,902	74.1	1,537,004	81.0
Institutional	1,712,795	21.4	866,271	50.6	360,731	19.0
5k	1,042,181	13.1	751,601	72.1	256,848	13.5
5k-10k	1,333,425	16.7	1,059,435	79.4	307,280	16.2
10k-50k	3,202,045	40.1	2,390,610	74.7	801,410	42.2
50k-100k	698,390	8.7	450,256	64.5	171,466	9.0
100k-500k	856,618	10.7	447,593	52.2	190,098	10.0
500k-1MM	281,761	3.5	150,160	53.3	59,646	3.1
1MM+	574,416	7.2	268,518	46.7	110,987	5.8
Total	7,988,836	100.0	5,518,173	69.1	1,897,735	100.0

Panel B: Percentage of IRT types and mean RTC for each type

Trade size	B/S		B/D		D/S	
	%	RTC	%	RTC	%	RTC
all	14.61	1.20	24.69	0.52	41.19	0.67
5k	10.69	1.87	29.14	0.62	38.92	0.68
5k-10k	14.78	2.02	25.88	0.62	42.90	0.73
10k-50k	12.19	1.57	25.23	0.56	46.88	0.74
50k-100k	12.33	0.76	24.97	0.45	44.25	0.63
100k-500k	15.07	0.31	22.56	0.31	34.25	0.43
500k-1MM	25.73	0.25	17.50	0.20	23.20	0.25
1MM+	37.47	0.21	14.27	0.13	17.50	0.16

Table10: The impact of rating downgrades announcements on bond liquidity.

This table reports the impact of rating downgrades on Amihud and RTC illiquidity measures. The rating changes are clustered at the firm level. The event study sample includes 3,581 downgrades by Moody's, S&P and Fitch during the period from July 2002 to September 2014. Panel A shows the liquidity impact of downgrades using the entire sample. Panel B shows the impact of downgrades within the investment grade category, Panel C shows the impact of downgrades within the non-investment grade category and Panel D shows the impact of downgrades that move the firm out of the investment grade category.

Event Window (days)	CAIL (Amihud)			CAIL(RTC)		
	N	*Mean*	*Median*	*N*	*Mean*	*Median*
[-20,-11]	526	$0.89^{t(***),s(*)}$	-0.11	428	$1.53^{t,\ s(***)}$	$1.11^{(***)}$
[-10,-1]	916	$1.93^{t,\ s(***)}$	$0.37^{(***)}$	754	$3.52^{t,\ s(***)}$	$2.41^{(***)}$
[0,+1]	946	$1.62^{t,\ s(***)}$	-0.00	768	$3.40^{t,\ s(***)}$	$1.53^{(***)}$
[0,+10]	561	$3.29^{t,\ s(***)}$	$0.88^{(**)}$	452	$4.17^{t,\ s(***)}$	$3.12^{(***)}$
[+11,+20]	865	$4.25^{t,\ s(***)}$	$1.81^{(***)}$	717	$6.76^{t,\ s(***)}$	$4.61^{(***)}$
Panel B: Downgrades within IG category						
[-20,-11]	368	$0.67^{t(***)}$	-0.19	308	$1.12^{t,\ s(***)}$	$0.85^{(***)}$
[-10,-1]	667	$0.92^{t,\ s(***)}$	0.14	555	$1.69^{t,\ s(***)}$	$1.17^{(***)}$
[0,+1]	689	$0.20^{t(***)}$	$-0.11^{(***)}$	568	$0.46^{t,\ s(***)}$	$0.30^{(***)}$
[0,+10]	413	$0.99^{t(***),\ s(*)}$	-0.06	345	$1.32^{t,\ s(***)}$	$0.89^{(***)}$
[+11,+20]	629	$1.14^{t,\ s(***)}$	0.25	532	$1.72^{t,\ s(***)}$	$1.13^{(***)}$
Panel C: Downgrades within HY category						
[-20,-11]	102	0.55	-0.11	69	$0.91^{t(*)}$	0.61
[-10,-1]	157	$0.76^{t(*)}$	-0.18	120	$0.80^{t(*)}$	0.37
[0,+1]	152	-0.14	$-0.26^{(***)}$	118	0.13	-0.00
[0,+10]	92	$0.84^{t(*)}$	-0.05	67	0.43	0.73
[+11,+20]	152	0.18	-0.36	117	-0.28	-0.09
Panel D: Downgrades across the IG/HY border						
[-20,-11]	57	$1.69^{t,\ s(***)}$	0.97	51	$2.95^{t,\ s(***)}$	$1.85^{(***)}$
[-10,-1]	94	$1.75^{t,\ s(***)}$	$0.99^{(***)}$	80	$3.39^{t,\ s(***)}$	$3.56^{(***)}$
[0,+1]	108	$0.58^{t(***),\ s(*)}$	0.10	83	$1.19^{t,\ s(***)}$	$1.06^{(***)}$
[0,+10]	57	$3.65^{t,\ s(***)}$	$1.89^{(**)}$	41	$4.47^{t,\ s(***)}$	$2.55^{(***)}$
[+11,+20]	84	$1.72^{t,\ s(***)}$	$1.19^{(***)}$	68	$2.74^{t,\ s(***)}$	$2.56^{(***)}$

* indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level. *t* denotes t-test and *s* denotes signed-rank test.

Table11: The impact of rating upgrades announcements on bond liquidity.

This table reports the impact of rating upgrades on Amihud and RTC illiquidity measures. The rating changes are clustered at the firm level. The event study sample includes 1,556 upgrades by Moody's, S&P and Fitch during the period from July 2002 to September 2014. *CAIL* is the sum of the firm's daily abnormal bond illiquidity over the event window. Daily abnormal bond illiquidity is measured as the bond's daily illiquidity minus the contemporaneous illiquidity on an index of corporate bonds matched by rating and maturity. If a firm has multiple bonds affected by the same rating announcement, the firm's daily abnormal bond illiquidity is the average of abnormal illiquidity on its individual bond issues. Panel A shows the liquidity impact of upgrades using the entire sample. Panel B shows the impact of upgrades within the investment grade category, Panel C shows the impact of upgrades within the non-investment grade category and Panel D shows the impact of upgrades that move the firm in to the investment grade category.

Event Window (days)	CAIL (Amihud)			CAIL(RTC)		
	N	*Mean*	*Median*	*N*	*Mean*	*Median*
Panel A: Upgrades in whole sample						
[-20,-11]	232	-0.22$^{s(**)}$	-0.43	227	0.38	0.00
[-10,-1]	355	-0.31$^{s(***)}$	-0.49$^{(***)}$	349	-0.14	-0.38$^{(***)}$
[0,+1]	361	-0.15 $^{s(**)}$	-0.32$^{(***)}$	358	-0.39	0.00
[0,+10]	233	-1.01 $^{t(**),s(***)}$	-1$^{(**)}$	232	-0.03	-0.36
[+11,+20]	341	-0.79 $^{t(*),s(***)}$	-0.94$^{(***)}$	337	-0.90 $^{t(*),s(**)}$	-0.63$^{(***)}$
Panel B: Upgrades within IG category						
[-20,-11]	163	-0.23 $^{s(*)}$	-0.38$^{(***)}$	163	-0.27	-0.03
[-10,-1]	244	-0.15 $^{s(***)}$	-0.47$^{(***)}$	244	-0.05	-0.16$^{(*)}$
[0,+1]	237	-0.08 $^{s(***)}$	-0.28$^{(***)}$	237	-0.07 $^{s(**)}$	0.00$^{(*)}$
[0,+10]	158	-0.64 $^{t\ ,s(***)}$	-0.66$^{(***)}$	158	-0.43 $^{t(*),s(**)}$	-0.59$^{(***)}$
[+11,+20]	230	-0.09 $^{s(**)}$	-0.47$^{(***)}$	230	-0.27 $^{s(*)}$	-0.30$^{(***)}$
Panel C: Upgrades within HY category						
[-20,-11]	55	-0.15 $^{s(*)}$	-0.46	52	1.92 $^{t\ ,s(***)}$	1.49
[-10,-1]	75	-0.41 $^{s(*)}$	-0.33	72	-0.03	0.00
[0,+1]	82	-0.02	-0.19$^{(*)}$	79	0.01	0.00
[0,+10]	59	-0.27	-0.51$^{(*)}$	58	0.28	-0.57
[+11,+20]	72	-0.82 $^{t,s(**)}$	-0.89$^{(**)}$	71	-0.66	-0.35
Panel D: Upgrades across the IG/HY border						
[-20,-11]	14	-0.24	0.14	12	-0.97	-0.84
[-10,-1]	36	-0.37	-0.33	33	0.39	0.38
[0,+1]	43	-0.47 $^{t(*),s(**)}$	-0.43$^{(**)}$	43	-0.23	0.00
[0,+10]	16	-1.84 $^{t(*),s(*)}$	-0.67	16	0.44	-0.11
[+11,+20]	40	-0.38	-0.71	37	0.21	0.00

Table 12: The impact of credit rating changes on bond liquidity: Normal vs. Recession period.

This table reports the impact of rating changes on Amihud and RTC illiquidity measures during the period before and after the recent financial crisis which is named as normal period (Panel A and Panel C) versus the recession period (Panel B and Panel D). The great recession starts from Dec 2007 and ends in June 2009. The rating changes are clustered at the firm level. *CAIL* is the sum of the firm's daily abnormal bond illiquidity over the event window. Daily abnormal bond illiquidity is measured as the bond's daily illiquidity minus the contemporaneous illiquidity on an index of corporate bonds matched by rating and maturity.

Event Window	CAIL (Amihud)			CAIL(RTC)		
(days)	*N*	*Mean*	*Median*	*N*	*Mean*	*Median*
Downgrades						
Panel A: Downgrades during normal period						
[-20,-11]	347	0.53 $^{t(***)}$	-0.11	272	1.65 $^{t,s(***)}$	0.97$^{(***)}$
[-10,-1]	641	0.63 $^{t,s(***)}$	0.04	505	2.13 $^{t,s(***)}$	1.39$^{(***)}$
[0,+1]	668	0.07 $^{s(*)}$	-0.12$^{(***)}$	521	0.61 $^{t,s(***)}$	0.42$^{(***)}$
[0,+10]	393	0.8 $^{t(***),s(**)}$	-0.06	298	1.88 $^{t,s(***)}$	1.54$^{(***)}$
[+11,+20]	605	0.65 $^{t,s(***)}$	-0.02	486	1.84 $^{t,s(***)}$	1.22$^{(***)}$
Panel B: Downgrades during the recession period						
[-20,-11]	179	1.19 $^{t(***)}$	0.07	156	0.73 $^{t,s(**)}$	0.45
[-10,-1]	275	1.76 $^{t,s(***)}$	0.82$^{(**)}$	249	0.93 $^{t,s(***)}$	0.72$^{(*)}$
[0,+1]	278	0.47 $^{t(***)}$	-0.01	247	0.24 $^{t(**),s(*)}$	0.23$^{(*)}$
[0,+10]	168	2.20 $^{t,s(***)}$	0.72	154	0.67 $^{t(*)}$	0.39
[+11,+20]	260	1.91 $^{t,s(***)}$	1.11$^{(***)}$	231	0.77 $^{t,s(***)}$	0.34
Upgrades						
Panel C: Upgrades during normal period						
[-20,-11]	212	-0.23 $^{s(**)}$	-0.39$^{(***)}$	207	0.26	-0.01
[-10,-1]	320	-0.38 $^{t,s(***)}$	-0.48$^{(***)}$	314	-0.04	-0.14
[0,+1]	341	-0.12 $^{s(***)}$	-0.29$^{(***)}$	338	-0.06 $^{s(*)}$	0.00$^{(**)}$
[0,+10]	217	-0.63 $^{t,s(***)}$	-0.58$^{(***)}$	216	-0.13 $^{s(*)}$	-0.56$^{(**)}$
[+11,+20]	303	-0.4 $^{t,s(***)}$	-0.62$^{(***)}$	229	-0.30	-0.29$^{(***)}$
Panel D: Upgrades during recession period						
[-20,-11]	20	-0.09	-0.13	20	-0.54	-0.03
[-10,-1]	35	1.12 $^{t(*)}$	-0.08	35	0.34	0.02
[0,+1]	20	-0.01	-0.08	20	-0.13	-0.24
[0,+10]	16	-0.61	-0.72	16	-1.11	-0.90
[+11,+20]	38	0.70	0.61	38	-0.28	-0.32

Table13: Determinants of corporate bond market illiquidity around downgrade events.

This table reports the results of OLS regressions for testing the effect of various bond level, firm level and market related factors on corporate bonds abnormal illiquidity around downgrade events. The dependent variable is *CAIL* over the [0, +10] days window around downgrade event. *CAIL* is the sum of the firm's daily abnormal bond illiquidity over the event window. Crisis is a dummy variable that takes the value of one if the downgrade happens during the period from Dec. 2007 to June 2009 and zero otherwise. *CAIL (-20,-10)>0*is a dummy variable equal to one if the firm's cumulative abnormal illiquidity over day -20 to -10 is greater than zero, and zero otherwise. *# of grades* is the absolute value of the number of grades that the rating is decreased by the downgrade. *Cross Inv/Spec border* is a dummy variable equal to one if the downgrade moved the firm out of the investment grade category. *Moody's* (*S&P*) is a dummy variable equal to one if the downgrade is a Moody's (S&P) downgrade and zero otherwise. *Old rating: Baa / Old rating: HY* are dummy variable equal to one if the pre-downgrade letter rating class is Baa/in high yield category. *# of bonds* is the number of bonds of the firm that are affected by the downgrade. *#customer sell (#customer buy)* is the average number of daily customer sells (buys) across all the bonds of the firm that are affected by the downgrade over the [0,+10] days window around rating event.

	CAIL (Amihud)			CAIL (RTC)		
	(1)	(2)	(3)	(1)	(2)	(3)
Crisis	1.277**	1.623***	2.059***	-1.103**	-0.711	0.360
$\boldsymbol{CAIL\ (-20,-10) > 0}$			3.301***			4.106***
<u>*Rating variables*</u>						
# of grades	0.859***	0.831***	1.315***	0.409*	0.405*	0.012
Cross Inv/Spec border	1.690*	1.224	-0.932	1.832*	1.706*	0.176
Moody's	0.053	-0.144	-0.750	-0.340	-0.516	-2.029***
S&P	0.575	0.623	-0.633	0.536	0.763	-0.746
Old rating: Baa	-0.413	-0.808	-0.043	0.081	-0.454	1.572*
Old rating: HY	-0.969	-1.549**	-1.823*	-1.775**	-1.574**	-1.262
# of bonds	0.424***	0.320**	0.254	0.273*	0.069	-0.106
<u>*Trading activity variables*</u>						
#customer sell		0.510***	0.572***		0.197**	0.107
#customer buy		-0.023	-0.07		0.167***	0.121***
volume		-0.057	-0.055		-0.114***	-0.101*
<u>*Issue/ Issuer characteristics*</u>						
Issue size	-1.831***	-2.113***	-1.943**	-1.301**	-1.159**	-1.52*
Coupon	0.337	0.299	0.467	0.449*	0.379*	0.111
Maturity	0.001	0.003	-0.056	0.034	0.050	0.061
Age	0.124*	0.119*	0.077	-0.053	-0.074	-0.74
Utility	-0.787	-0.200	1.273	2.941***	4.233***	4.720**
Finance	1.401**	1.298**	0.556	0.877	0.756	0.911
Intercept	-4.370***	-4.301***	-5.832***	-2.014	-2.091	-1.205
Obs	561	561	276	452	452	206
Adjusted R^2	0.12	0.16	0.29	0.08	0.17	0.33

* indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level

Table 14: Determinants of corporate bond market illiquidity around upgrade events.

This table reports the results of OLS regressions for testing the effect of various bond level, firm level and market related factors on corporate bonds abnormal illiquidity around upgrade events. The dependent variable is *CAIL* over the [0, +10] days window around upgrade event. *CAIL* is the sum of the firm's daily abnormal bond illiquidity over the event window. Crisis is a dummy variable that takes the value of one if the upgrade happens during the period from Dec. 2007 to June 2009 and zero otherwise. *CAIL (-20,-10)<0*is a dummy variable equal to one if the firm's cumulative abnormal illiquidity over day -20 to -10 is greater than zero, and zero otherwise. *# of grades* is the absolute value of the number of grades that the rating is increased by the upgrade. *Cross Inv/Spec border* is a dummy variable equal to one if the upgrade moved the firm out of the investment grade category. *Moody's* (*S&P*) is a dummy variable equal to one if the upgrade is a Moody's (S&P) upgrade and zero otherwise. *Old rating: Baa / Old rating: HY* are dummy variable equal to one if the pre-upgrade letter rating class is Baa/in high yield category. *# of bonds* is the number of bonds of the firm that are affected by the upgrade. *#customer sell (#customer buy)* is the average number of daily customer sells (buys) across all the bonds of the firm that are affected by the upgrade over the [0,+10] days window around rating event.

	CAIL (Amihud)			CAIL (RTC)		
	(1)	(2)	(3)	(1)	(2)	(3)
Crisis	0.667	0.657	0.156	-1.152	-1.284	-1.183
$CAIL\ (-20,-10) < 0$			-1.146*			-1.681**
<u>*Rating variables*</u>						
# of grades	-0.127	-0.116	0.596*	0.344*	0.245	0.861**
Cross Inv/Spec border	-1.498*	-1.345*	-0.903	0.321	0.722	2.007
Moody's	0.080	0.143	-0.412	0.698	0.683	1.408*
S&P	-0.934**	-0.969**	-0.893	-0.684	-0.846	-0.174
Old rating: Baa/BBB	-0.889*	-0.658	-0.255	0.052	0.261	0.511
Old rating: HY	-0.779	-0.688	-0.517	-0.962	-1.565**	-2.546**
% of bonds	0.246	0.148	-0.131	0.428**	0.267	0.418
<u>*Trading activity variables*</u>						
#customer sell		0.289	0.406		0.671***	0.639**
#customer buy		-0.061	-0.475**		0.227	-0.016
volume		-0.194***	-0.081		-0.166**	-0.089
<u>*Issue/ Issuer characteristics*</u>						
Issue size	-1.715***	-0.970	0.100	-1.293*	-1.604**	-1.858
Coupon	0.098	0.073	-0.211	0.415*	0.387*	0.103
Maturity	-0.008	0.006	0.013	0.040	0.06**	0.162***
Age	0.135**	0.094*	0.177**	0.063	0.017	0.026
Utility	1.860*	1.662*	0.501	-0.551	-0.856	-5.522**
Finance	0.606	0.662	0.159	-0.070	-0.423	-2.535**
Intercept	-1.422	-1.088	0.325	-3.935***	-3.402**	-0.752
Obs	233	2.33	102	232	232	100
Adjusted R^2	0.165	0.198	0.189	0.121	0.168	0.318

* indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

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Corporate Bond Pricing and Liquidity: A Review

By

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ABSTRACT

This paper reviews the large and growing literature on the impact of liquidity on corporate bond pricing and yield spreads. Our discussion covers both theoretical and empirical papers in this field. We start by a brief review of the concept and models of liquidity and follow by a review on the impact of liquidity on asset prices. Next, we focus on corporate bond market and review theoretical as well as empirical researches contributing to the field.

1. Introduction

There is a huge theoretical and empirical literature that explores the impact of corporate bonds' Credit risk on its' yield spread, the spread between the yield of a corporate bond and the yield of the risk free bond with comparable characteristics, which has its' origin in the structural credit risk models pioneered by the work of Black and Scholes (1963) and Merton (1974). However as empirically demonstrated by Jones, Mason, and Rosenfeld (1984), Black Scholes Merton model generates credit spreads that are smaller than actually observed. As such, many academics have tried to expand the original model by incorporating more realistic features of corporate debt. Some important works in this area include Black and Cox (1976), Geske (1977), Geske and Johnson (1984), Longstaff and Schwarts (1995), Leland (1994), Leland and Toft (1996) and Collin- Dufrense and Goldstein (2001) among others.

Also, a growing body of literature has focused on the "non-default component" of yield spreads for explaining the "credit spread puzzle" that arises from Merton (1974) model. Their findings suggest that the "non-default component" is strongly associated with liquidity measures. Usually in these studies credit spread is treated as a combination of two parts: "default premium" and "liquidity premium" and the impact of each component on the cross sectional and time series variations of credit spread is empirically measured (e.g. Longstaff, Mithal, and Neis, 2005; Friewald, Jankowitsch and Subrahmanyam, 2009; by Bao, Pan and Wang, 2011; Dick-Nielsen, Feldhutter and Lando, 2012).

This paper reviews the literature related to the key theoretical and empirical researches that model and quantify the liquidity component of yield spreads including some recent studies that focus on the role of illiquidity during the recent financial crisis.

First, we start by a brief background of the concept and theoretical models of liquidity in section 2. Section 3 gives an overview of the studies on the impact of liquidity on asset prices. In section 4, we turn our focus to corporate bond market and review structural credit risk models including the recent ones including liquidity either as an exogenous shock or an endogenous risk factor. Section 5 reviews the empirical studies on bond pricing and liquidity.

2. Models of liquidity

Liquidity is one of the key concepts in securities markets which is often a desirable feature and reflects a well-functioning market. At the same time it is not directly observable from the market data and is not easily measurable. Based on the intuitive but wage definition of Keynes, an asset is liquid if "it is more certainly realizable at short notice without loss."

Market liquidity hinges in large part on whether market-makers respond to temporary imbalances in supply and demand by stepping in as buyers (or sellers) against trades sought by other market participants. The role of market makers as liquidity providers and price setting agents was originally studied in the traditional inventory based models of market microstructure. Researchers have typically followed three broad approaches to model liquidity and how prices are set by market makers. One approach is inventory based modeling. The inventory based models view the trading process as a matching problem in which the market maker or price setting agent must use prices to balance supply and demand across time. There are several distinct modeling approaches in this area. For example Garman (1976) focus on the nature of order flow. Stoll (1978) examine the optimization problem facing dealers and Cohen, Maier, Schwartz and Whitcomb (1981) analyze the effect of multiple providers for immediacy. Common to all these models are uncertainties in order flow, which can result in inventory problems for market maker and execution problem for dealers.

Amihud and Mendelson (1980), Ho and Stoll (1981, 1983), Mildenstein and Schleef (1983), and Grossman and Miller (1988) examined the impact of inventories on liquidity provision. Based on Grossman and Miller (1988), market liquidity is determined by the demand and supply of immediacy. In their setting, exogenous liquidity events and the risk of delayed trade create a demand for immediacy. Market makers supply immediacy by their presence and willingness to take inventory risk during the period between the arrival of final buyers and sellers. The number of market makers is adjusted in the long run to determine the equilibrium level of liquidity in the market. They show that the lower is the autocorrelation in rates of return, the higher is the equilibrium level of liquidity.

In general, inventory models without capital constraints predict that liquidity (the width of the bid-ask spread) is not affected by the market maker's inventory position, but there are exceptions (e.g. Amihud and Mendelson 1980; Shen and Starr (2002). O'Hara and Oldfield (1986) show that spreads depend on inventories if market makers are risk-averse. Even models that do not predict a link between inventories and the width of the spread can generate time variation in liquidity, as a market maker's desire to supply liquidity is typically a function of an asset's fundamental volatility.

A second approach is related to the effect of asymmetric information on market prices. If some traders are better informed about the underlying value of an asset, their trades could reveal the information and affects the behavior of prices. This approach is followed by Kyle (1984, 1985), Glosten and Milgrom (1985) and Easley and O'Hara (1987) among others.

The third and more recent approach focuses on funding costs and financing constraints of market makers. In a model with margin constraints, Gromb and Vayanos (2002) show how arbitrageurs' liquidity provision benefits all investors. Coughenour and Deli (2002) examine the influence of the organizational form of the NYSE specialist firms on the nature of liquidity provision. They compare closely held firms whose specialists provide liquidity with their own capital to widely held firms whose specialists provide liquidity with diffusely owned capital. They argue that specialists using their own capital have a greater incentive and ability to reduce adverse selection costs, but face a greater cost of capital.

Weill (2007) examines dynamic liquidity provision by market makers and shows that competitive market makers offer the socially optimal amount of liquidity, if they have access to sufficient capital. In his model, at time zero, outside investors receive an aggregate shock which lowers their marginal utility for holding assets relative to cash. This creates a sudden need for cash and induces a large selling pressure. Then, randomly over time, each investor recovers from the shock, implying that the initial selling pressure slowly disappears. The asset market can be illiquid in his model in the sense that investors make contact with market makers only after random delays. In this economic environment, market makers offer buyers and sellers "immediacy". Market makers anticipate that after the selling pressure subsides, they will achieve contact with more buyers than sellers, which will allow them then to transfer assets to buyers in two ways. Therefore, by accumulating inventories early, when the selling pressure is large, market makers mitigate the adverse impact on investors of execution delays. The socially optimal asset allocation maximizes the sum of investors' and market makers' intertemporal utility, subject to the order-execution technology. He shows that if marketmakers maintain sufficient capital, the socially optimal allocation is implemented in a competitive equilibrium. However, If marketmakers do not maintain sufficient capital, then they are not able to purchase as many assets as prescribed by the socially optimal allocation.

Brunnermeier and Pedersen (2009) construct a model along the lines of Grossman and Miller (1988) that also links an asset's market liquidity and traders' funding liquidity. The ability of market makers to provide liquidity depends on their access to funding. Conversely, dealers' funding and their capital and margin requirements, depends on the assets' market liquidity. They show that, under certain conditions, margins are destabilizing and market liquidity and funding liquidity are mutually reinforcing, leading to liquidity spirals. Furthermore they show that limited risk-bearing capacity can have a differential impact on high and low fundamental volatility stocks. They use the term "flight to quality" to refer to the result that the liquidity differential between high and low volatility securities is greater when market makers have taken on larger positions or when market-maker wealth decreases. Flight-to-quality evidence is also present in Pastor and Stambaugh (2003).

3. Liquidity and asset prices

Based on the discussion provided in the previous section, dealers' bid-ask spread (quoted or effective) which is defined as the difference in price between the highest price that a buyer is willing to pay and the lowest price for which a seller is willing to sell an asset, is commonly used as a measure of liquidity. Illiquidity can be measured by the cost of immediate execution. An investor willing to transact faces a tradeoff. He may either wait to transact at a favorable price or insist on immediate execution at the current bid or ask price. The quoted ask (offer) price includes a premium for immediate buying and the bid price similarly reflects a concession required for immediate sale. Thus the spread between the bid and ask prices can be a natural measure of illiquidity.

Roll (1984) gives a measure of effective bid-ask spread assuming an efficient market ($Spread = 2\sqrt{-cov}$) in which cov is the first order serial covariance of successive price changes. This equation implies that the spread can be inferred from the sequence of price changes by computing and transforming serial covariance. Since collecting the bid-ask spreads from the market data is a costly procedure he validates this result indirectly by relating the measured implicit spread to firm size. Firm size is positively related to volume and volume is negatively related to spread. So there should be a strong negative cross sectional relation between measured spread and measured size which is confirmed by empirical results. Another interesting point in this paper is that using daily data, the average value of the implicit bid-ask spread across all stocks and time periods was only 0.298 percent. But the average implicit bid-ask spread estimated from weekly returns was 1.74 percent which is proved to be significantly different from 0.298. Since the spread inferred from any observation intervals must be equal when the market is informationally efficient, these results cast doubt on the efficiency of the New York and American Exchanges which are considered in this research.

Amihud and Mendelson (1986) studied the effect of the bid-ask spread on asset pricing. They showed that market observed expected return is an increasing and concave function of the spread. Their model predicts that higher spread assets yield higher expected returns and that there is a clientele effect whereby investors with longer holding periods select assets with higher spreads. The prediction offered by their model can be tested by estimating the following regression for a portfolio j of assets:

$$Rt(j) = c + t(j) + logSt(j) \ (1)$$

Where $Rt(j)$ denotes the average monthly rate of return on a stock included in the portfolio j in excess of the 90-day return on Treasury bonds, $t(j)$ is the beta coefficient for portfolio j, and $St(j)$ is the average bid-ask spread. The empirical analysis based on estimates for (1) shows a high level of significance for all the arguments of the regression. Their research highlights the importance of securities market microstructure in determining asset returns and provides a link between this area and mainstream research on capital markets.

Also Amihud and Mendelson (1988, 1991) show that average portfolio returns increase with the spread, and the spread effect persists if firm size is included in equation (1) as an additional variable.

In Amihud (2002), time-series effect of liquidity on stock returns is considered as well as the cross sectional effect which had been previously explored by other researchers. This study suggested that over time, the ex-ante stock excess return is increasing in the expected illiquidity of the stock market, suggesting that expected stock excess return which is traditionally called risk premium and has been considered a compensation for risk, partly represents an illiquidity premium (a compensation for expected market illiquidity). He proposed the ILLIQ measure of illiquidity which is the daily ratio of absolute stock return to its dollar volume, averaged over some period (a rough measure of price impact). It can be interpreted as the daily price response associated with one dollar of trading volume. According to the results both across stocks and over time, expected stock returns are an increasing function of expected illiquidity. Across NYSE stock during 1964-1997, ILLIQ has a positive and highly significant effect on expected return. Results also show that unexpected market illiquidity lowers contemporaneous stock prices. This illiquidity effects are shown to be stronger for small firms stocks. This suggests that variations over time in size effect, are related to changes in market liquidity over time. The negative effect of unexpected illiquidity is observed because higher realized illiquidity raises expected illiquidity which in turn leads to higher stock expected returns. Then stock prices should decline to make the expected return rise (assuming that corporate cash flows are unaffected by market liquidity).

In another study Huang (2002) shows that illiquidity can have large effects on asset returns when agents face liquidity shocks and borrowing constraints.

Pastor and Stambaugh (2003) also investigated whether market wide liquidity is a state variable important for asset pricing. In order to construct their individual measure of illiquidity they focused on a dimension of liquidity associated with temporary price changes accompanying order flow. They obtained the measure of market liquidity in a given month as the equally weighted average of the liquidity measures of individual stocks in NYSE and AMEX, using daily data within the month.

The aggregate measure was then regressed on its lag as well as the lag of the scaled level series and the fitted residual of this regression is taken as the innovation in liquidity. They defined liquidity beta as the coefficient on liquidity innovation in a regression that also includes the three factors of Fama and French. The results suggest the following points: expected stock returns are related cross sectionally to the sensitivities of returns to fluctuations in aggregate liquidity. Stocks that are more sensitive to aggregate liquidity have substantially higher expected returns even after accounting for exposures to the market return, size, value and momentum factors and liquidity risk factor accounts for half of the profits to a momentum strategy over the period of 1966 to 1999.

Acharya and Pedersen (2005) proposed a liquidity adjusted capital asset pricing model. Their model provides a unified theoretical framework that helps understand the various channels through which liquidity risk may affect asset pricing and can explain the previous empirical findings that :

- Return sensitivity to market liquidity is priced.(Pastor and Stambaugh,2003)

- Average liquidity is priced.(Amihud and Mendelson,1986)
- Liquidity co-moves with return and predict future returns (Amihud, 2002; Chordia et al, 2001a; Jones, 2001; Bekaert et.al.2003).

In their asset pricing model, three liquidity betas are included based on three liquidity risk components: commonality in liquidity with market liquidity, return sensitivity to market liquidity and liquidity sensitivity to market returns. They use Amihud ILLIQ measure as liquidity proxy in their study. Their results show that liquidity adjusted CAPM explains the data better than the standard CAPM, while still exploiting the same degree of freedom. Positive shocks to illiquidity, if persistent, are associated with a low contemporaneous returns and high predicted future returns. They also found a weak evidence that liquidity risk is important over and above the market risk and the level of liquidity. According to their findings, liquidity risk explains about 1.1 percent of cross sectional returns and about 80 percent of this effect is due to the liquidity sensitivity to the market return.

Lou and Sadka (2010) show that the performance of stocks during the financial crisis can be better explained by their historical liquidity betas as measured by the covariation of their return with unexpected changes in aggregate liquidity. Their findings show that although considered safe assets in general, liquid stocks underperformed illiquid stocks during the financial crisis of 2008-2009. These findings highlight the importance of accounting for both liquidity level and liquidity risk in risk management applications.

Brunnermeier and Pedersen (2009) provided a model that relates market liquidity and funding liquidity. While market liquidity of an asset is the ease with which it is traded, traders funding liquidity is the ease with which they can obtain funding. Traders provide market liquidity and their ability to do so depends on their availability of funding. Conversely traders funding (their capital and margin requirements), depends on the asset market liquidity. Their proposed model explains the empirically documented features that market liquidity can suddenly dry up, has commonality across securities, is related to volatility, is subject to flight to quality and co-moves with the market.

4. Structural credit risk models and credit spread puzzle

In Section 3, we discussed papers studying the impact of liquidity on securities prices. While the studies reviewed in previous section were mostly related to stock market, we now turn our focus to corporate bonds. The literature on corporate bond pricing and bonds' yield spread which is commonly referred to as 'credit spread' has its root in the pioneering work of Merton (1974) which utilized the Black and Scholes (1963) option pricing model to derive the value of firms' equity and debt. However it is widely recognized that the observed difference between the yield of a corporate bond and the yield of a risk free government bond with comparable maturities is wider than what is predicted by the structural credit risk model of Merton (1974) particularly for investment grade bonds. This difference between the actual credit spreads and the spreads predicted by the structural models gives rise to the 'credit spread puzzle' which has stimulated the academics to study the non-default component of credit spreads (eg. Longstaff and Schwartz, 1995a; Duffie and Singleton,1997; Goldstein, and Martin, 2001; Collin-Dufresne, Goldstein, and Helwege, 2003 among many others).

Recently, few studies have developed structural credit risk models incorporating secondary market illiquidity. The first paper along this line is He and Xiong (2012) which examines the effect of bond market liquidity deterioration on the firm's credit risk. Their model builds on the structural credit risk model of Leland (1994) and Leland and Toft (1996) which is based on the endogenous default notion of Black and Cox (1976). Briefly explained, the endogenous default concept is as follows: When a bond matures, the firm issues a new bond with the same face value and maturity to replace it at the market price, which can be higher or lower than the principal of the maturing bond. This rollover gain/loss is absorbed by the firm's equity holders. As a result, the equity price is determined by the firm's current fundamental (i.e., the firm's value when it is unlevered) and expected future rollover gains/losses. When the equity value drops to zero, the firm defaults endogenously and bond holders can only recover their debt by liquidating the firm's assets at a discount. Based on the above explanation, one can imagine a positive feedback loop between price and credit quality.

In He and Xiong (2012), an exogenous liquidity shock triggers the endogenous default: Bond holders are subject to Poisson liquidity shocks. Upon the arrival of a liquidity shock, a bond holder has to sell his holdings at a proportional cost. The trading cost multiplied by bond holders' liquidity shock intensity determines the liquidity premium in the firm's credit spread. The increased liquidity premium (i.e. Decreased secondary market price) feeds back to the primary market and suppresses the market price of the firm's newly issued bonds and increases equity Holders' rollover losses.

In another paper, He and Milbradt (2014) expand He and Xiong (2012) framework and introduce the concept of endogenous liquidity. Their rationale on how a decline in firms' credit quality affects bond liquidity is based on endogenous bid-ask spread notion of Duffie, Gârleanu, and Pedersen (2005). Two types of investors exist in their model: high type and low type. High type investors are the ones that incur no cost for holding the asset. Low type investors are the ones affected by an exogenous liquidity shock and incur holding cost, so they search for a dealer to get rid of the bond. Chen, Cui, He and Milbradt (2015) model this holding cost in light of collateralized borrowing and assume that the bond is part of a large portfolio including leverage and can be used as collateral for these loans. Borrowing against the bond involves haircut. The decline in bonds credit quality pushes down its market price and increases the haircut. This in turn drives down the low type investor valuation of the bond and widens the valuation wedge between high type and low type investors. Since the bid-ask spread in their model is a function of investors bargaining power and the valuation wedge between low type and high type investors, the above procedure results in a rise in the bid-ask spreads. They further propose a structural decomposition that nests the common additive default-liquidity decomposition to quantify the interaction between default and liquidity for corporate bonds. Similar to Longstaff et al. (2005), using CDS spread to proxy for default risk, they identify the "default" part by pricing a bond in a counterfactually perfectly liquid market but with the model implied default threshold. They identify the remaining credit spread after subtracting this "default" part as the "liquidity" part. Then they further decompose the "default" ("liquidity") part into a "pure default" ("pure liquidity") component and a "liquidity-driven-default" ("default-driven liquidity") component, where the "pure default" or "pure liquidity" part is the spread implied by a counterfactual model where either the bond market is perfectly liquid as in Leland and Toft (1996) hence equity holders default later, or only the over-the-counter search friction for risk free bonds is at work as in Duffie et al. (2005), respectively. The two interaction terms that emerge, i.e., the "liquidity-driven default" and the "default-driven liquidity" components, capture the endogenous positive spiral between default and liquidity.

5. Empirical studies on bonds liquidity premium

A growing stream of empirical research related to both corporate bond pricing and liquidity is related to the credit spread puzzle. Credit spread is the component of corporate bond yields that is above and beyond the yield of comparable default free treasury bonds. In other words excess interest rate that would be earned if the corporation does not default and the investor holds the bond to maturity.

This definition suggests that credit spread is supposed to reflect the financial health of the firm that issued the bond. As discussed in the previous section, in practice, empirical researchers have only been able to explain less than half of the variation in credit spreads and therein lays the credit spread puzzle. In explaining the puzzle researchers have turned their attention to non default rated factors that would be common to the credit spreads of most firms in the economy. One of these factors is the tax difference between interest earned on corporate and treasury bonds. Another factor that may contribute to the yield spread between corporate bonds and Treasury securities, is related to notable difference between the liquidity level of corporate bonds with that of the Treasury securities with similar maturity. The volume of transaction for corporate bonds is far less than for treasury securities. Moreover the information content of bond prices tend to be lower for less actively traded securities. For corporate bonds, compensation for liquidity risk shows up in higher interest rate spreads over otherwise comparable treasury bonds. The financial crisis of 2008 has brought renewed interest and a sense of urgency to this topic as concerns over both illiquidity and credit risk intensified at the same time and it was not clear which factor was the dominating force in driving up corporate bond spreads. The aggregate illiquidity doubled from its pre-crisis average in August 2007 when the credit problem first broke out. By September 2008, it was five times it pre crisis average and over 12 standard deviations away.

Longstaff, Mithal, and Neis (2005) find that the non-default component is time varying and strongly related to measures of both bond-specific liquidity and aggregate bond market liquidity. Calculating spreads relative to the Treasury curve, they find that the non-default component represents 17 percent for BB-rated bonds, 29 percent for BBB-rated bonds, 44 percent for A-rated bonds and 49 percent of the spread for AAA/AA rated bonds. After financial crisis of 2007-2009 a number of studies have investigated the relative importance of liquidity component vs. default component of credit Spreads during the financial crisis.

In a research conducted by Edwards et al. (2007), a complete record of US over-the-counter (OTC) secondary trades in corporate bonds is used to estimate average transaction costs as a function of trade size. Findings suggest that transaction costs decrease significantly with trade size. Highly rated bonds, recently issued bonds and bonds close to maturity have lower transaction costs than do other bonds and costs are lower for bonds transparent trade prices.

Dick-Nielsen, Feldhütter and Lando (2012) analyzed liquidity components of corporate bond spreads during 2005-2009 and found that the spread contribution from illiquidity increases dramatically with the onset of the subprime crisis. According to their results the increase is slow and persistent for investment grade bonds while the effect is stronger but more short-lived for speculative grade bonds.

Similar results for the crisis period are obtained by Bao, Pan and Wang (2011). Using transactions data from 2003 to 2009, they examine the illiquidity of corporate bonds and its asset pricing implications. They show that in aggregate, changes in market level illiquidity explain a substantial part of the time variation in yield spreads of high rated (AAA through A) bonds, overshadowing the credit risk component. In the cross section, the bond level illiquidity measure explains individual bond yields spreads with large economic significance. They also find that bond illiquidity is related to several bond characteristics. In particular illiquidity increases with a bonds age and maturity but decreases with its issuance size. Price reversals are inversely related to trade size (price changes accompanied by small trades, exhibit stronger reversals than those accompanied by large trades). According to their results, while during normal times aggregate liquidity and aggregate credit risk are equally important in explaining yield spreads of high rated bonds, illiquidity becomes much more important during the 2008 crisis. Relating this observation to the discussion on whether the 2008 crisis was mainly a liquidity or credit crisis, these results suggest that as far as high rated corporate bonds are concerned, the sudden increase in illiquidity was the dominating factor in driving up the yield spreads. A measure of illiquidity, for each individual bond is constructed in this paper which is the negative of auto covariance in relative price changes (γ). The lack of liquidity in an asset gives rise to transitory components in its prices and thus the magnitude of such transitory price movements reflects the degree of illiquidity in the market. Because transitory price movements lead to negatively serially correlated price changes, γ gives a meaningful measure of illiquidity. As mentioned before, Roll (1984) first considered the simple case in which the transitory price movements arise from bid-ask bounce, where $Spread = 2\sqrt{-cov}$. But According to Bao et.al. (2011), in more general cases, γ captures the broader impact of illiquidity on prices above and beyond the effect of bid- ask spread.

Feldhütter (2012), uses the difference between prices paid by small traders and those paid by large traders as a measure to identify when the market price of an over-the-counter traded asset is below its fundamental value due to selling pressure. Using a structural estimation his model for OTC trading with search frictions and periods with selling pressures is able to identify liquidity crisis (i.e. high number of forced sellers in the US corporate bond market.)

Tsuji (2005) empirically tests the explanatory power of the factors implied by the theory on credit spreads, and presents the puzzle that such factors explain little of these spreads. Economically approaching this puzzle he tests the explanatory power of other economic factors such as credit rating, illiquidity, investors' preferences, and the business cycle.

Zheng (2006) discusses the interaction of default risk and liquidity risk on pricing financial contracts and shows that the two risks are almost indistinguishable if the underlying contract has non-negative values. However, if the underlying contract can take negative values as well, depending on their loss rates and distributions, these two risks demand different risk premiums. A structural default model and a discrete time default model with exponentially distributed liquidity shocks are discussed in this paper. Based on these models, short-term yield spreads are dominated by liquidity risk rather than credit risk. A two-stage procedure is suggested to calibrate the model with one scalar optimization problem and one linear programming problem.

Houweling, Mentink and Vorst (2005) used nine different proxies (issued amount, listed, euro, on-the-run, age, missing prices, yield volatility, number of contributors and yield dispersion) to measure corporate bond liquidity and used a four-variable model to control for interest rate risk, credit risk, maturity and rating differences between bonds. Based on a sample of euro corporate bonds, the null hypothesis that liquidity risk is not priced is rejected for eight of these liquidity proxies. Using a comparison test between liquidity proxies they found limited differences between the proxies.

Using a panel data for the period from year 1993 through 2008, Chen, Liao and Tsai (2011) showed that corporate internal liquidity risk significantly impacts bond yield spreads (and changes) when controlling for well-known bond yield determinant variables, traditional accounting measures of corporate debt servicing ability, cash flow volatility, credit ratings, and state variables. Their findings shows that internal liquidity risk should therefore be incorporated into bond yield spread modeling.

Lin, Wang and Wu (2011) studied the pricing of liquidity risk in the cross section of corporate bonds for the period from January 1994 to March 2009. Their results showed that the average return on bonds with high sensitivities to aggregate liquidity exceeds that for bonds with low sensitivities by about 4 percent annually. In their study, they control for the effects of default and term betas, liquidity level, and bond characteristics. They conclude that liquidity risk is an important determinant of expected corporate bond returns.

Gefang, Koop and Potter (2011) developed a structured dynamic factor model for the spreads between London Interbank Offered Rate (LIBOR) and overnight index swap (OIS) rates for a panel of banks. Their model involves latent factors which reflect liquidity and credit risk. Their results show that surges in the short term LIBOR-OIS spreads during the 2007-2009 financial crisis were largely driven by liquidity risk. However, credit risk played a more significant role in the longer term (twelve-month) LIBOR-OIS spread. The liquidity risk factors show more volatility than the credit risk factor. They argued that most of the familiar events in the financial crisis were linked more to movements in liquidity risk than credit risk.

Kalimipalli and Nayak (2012) empirically investigated the relative effects of equity volatility and bond liquidity in the cross-section of corporate bond spreads and showed that while both volatility and liquidity effects are significant, volatility, representing ex-ante credit shock, has the first-order impact, and liquidity represented by bond characteristics and price impact measure has the secondary impact on bond spreads. Conditional analysis further reveals that distressed bonds and distressed regimes are both associated with significantly higher impact of volatility and liquidity shocks. They find that the relative impact of these effects depend both on the underlying bond characteristics and general market conditions.

Friewald, Jankowitsch and Subrahmanyam (2012) investigated whether liquidity is an important price factor in the US corporate bond market. Particularly they focus on liquidity effects in periods of financial crises, especially for bonds with high credit risk, using a data set of more than 20,000 bonds, between October 2004 and December 2008. Using different liquidity measures, they find that liquidity effects account for approximately 14 percent of the explained market-wide corporate yield spread changes and the economic impact of the liquidity measures is significantly larger in periods of crisis, and for speculative grade bonds.

Acharya, Amihud and Bharath (2013) studied the exposure of the US corporate bond returns to liquidity shocks of stocks and Treasury bonds over the period from 1973 to 2007 in a regime-switching model. Their findings suggest a heterogeneous effect of liquidity shocks on investment grade and speculative grade bond prices during different regimes. While in one regime, liquidity shocks show insignificant effects on bond prices, in another regime, an increase in illiquidity produces significant and conflicting effects: Prices of investment-grade bonds rise but prices of high yield bonds substantially fall relative to the market. Relating the probability of these regimes to macroeconomic conditions they found that the second regime can be predicted by economic conditions that are characterized as stress. While they control for other systemic risks, they find time-varying liquidity risk of corporate bond returns conditional on episodes of flight to liquidity. They also found a similar pattern for stocks classified by high or low book-to-market ratio, where again, liquidity shocks play a special role in periods characterized by adverse economic conditions.

Helwege, Huang and Wang (2013) tried to disentangle the credit risk factor and liquidity risk factor empirically. They separated out the credit risk component by examining bonds that are issued by the same firm and that trade on the same day, allowing us to examine the effects of liquidity in a sample of bond pairs. Testing standard liquidity measures to determine how well they explain the differences in the two bonds yield spreads, their findings suggest that the proxies do a poor job of measuring liquidity effects. Although incorporating liquidity proxies related to other bonds issued by the firm and those for bonds of other firms significantly improved the explanatory power, they still found a significant portion of the spread unexplained and largely driven by a common unknown factor. They conclude that good proxies for the liquidity component of corporate bond spreads remain elusive.

Kalimipalli, Nayak and Perez (2013) studied the dynamic impact of idiosyncratic volatility and bond liquidity on corporate bond spreads over time and empirically disentangled both effects. Using an extensive data set, they found that both idiosyncratic volatility and liquidity are critical mainly for the distress portfolios, i.e., low-rated and short-term bond. For other types of bonds, only volatility matters. According to their results, the effects of volatility and liquidity shocks on bond spreads were both exacerbated during the recent financial crisis and while volatility shocks are more persistent and have a long-term effect, liquidity shocks are quickly absorbed into bonds prices.

Chen, Liao and Kuo (2013) explored internal liquidity risk (ILR) and financial bullwhip effects on corporate bond yield spreads along supply chain counterparties by employing American market data from year 1997 to 2008. This study finds that the ILRs of suppliers and customers positively affect a firms bond yield spreads and the effects of customers ILRs are greater. They also found a financial bullwhip effect that the ILR effect becomes greater upwardly along the supply chain counterparties. These results were robust when controlling for well-known spread determinant variables.

References

Acharya, Viral V., and Lasse Heje Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* 77, 375-410.

Acharya, Viral V., Yakov Amihud, and Sreedhar T. Bharath, 2013, Liquidity risk of corporate bond returns: conditional approach, *The Review of Financial Studies* 110, 358-386.

Amihud, Yakov, and Haim Mendelson, 1980, Dealership market: Market making with inventory, Journal of Financial Economy 8, 31-53.

Amihud, Yakov, and Haim Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223-219.

Amihud, Yakov, and Haim Mendelson, 1988, Liquidity and asset prices: Financial management implications, Financial Management 17, 5-15.

Amihud, Yakov, and Haim Mendelson, 1991, Liquidity, maturity, and the yields on U.S. treasury securities, *The Journal of Finance* 46, 1411-1425.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets* 5, 31–56.

Bao, Jack, Jun Pan, and Jiang Wang, 2011, The illiquidity of corporate bonds. *The Journal of Finance* 66(3), 911–946.

Black, Fischer, and John C. Cox, 1976, Valuing corporate securities: Some effects of bond indenture provisions, *The Journal of Finance* 31, 351-367.

Black, Fischer, and Myron Scholes, 1973, The pricing of options and corporate liabilities, *The Journal of Political Economy* 81, 637-654.

Brunnermeier, M., and Lasse Heje Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22(6), 2201-2238.

Chen, Hui, Rui Cui, Zhiguo He, Konstantin Milbradt, 2015, Quantifying liquidity and default risks of corporate bonds over the business cycle, NBER Working Papers 20638.

Chen, Tsung-Kang, Hsien-Hsing Liao, and Pei-Ling Tsai, 2011, Internal liquidity risk in corporate bond yield spreads, *Journal of Banking and Finance* 35,978-987.

Chen, Tsung-Kang, Hsien-Hsing Liao , and Hui-Ju Kuo, 2013, Internal liquidity risk, financial bullwhip effects, and corporate bond yield spreads: Supply chain perspectives, *Journal of Banking and Finance* 37, 2434-2456.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2001, Market liquidity and trading activity, *The Journal of Finance* 56, 501-530.

Cohen, Kalman J., Steven F. Maier, Robert A. Schwartz, and David K. Whitcomb, 1981, Transaction costs, order placement strategy, and existence of bid-ask spread, Journal of political economy 89, 287-305.

Collin-Dufresne, Pierre, and Robert S. Goldstein, 2001, Do credit spreads reflect stationary leverage ratios?, The Journal of Finance 56, 1929-1957.

Collin-Dufresn, Pierre, Robert S. Goldstein, and J. Spencer Martin, 2001, The determinants of credit spread changes, *The Journal of Finance* 56, 2177-2207.

Coughenour, Jay F., and Daniel N. Deli, 2002, Liquidity provision and the organizational form of NYSE specialist firms, *The Journal of Finance* 57, 841-869.

Dick-Nielsen, Jens, Peter Feldhütter and David Lando, 2012, Corporate bond liquidity before and after the onset of the subprime crisis, *Journal of Financial Economics* 103(3), 471 –492.

Duffie, Darrell, and Kenneth J. Singleton, 1997, An econometric model of the term structure of interest-rate swap yields, *The Journal of Finance* 52, 1287-1321.

Duffie, Darrell, Nicolae Gârleanu, and Lasse Heje Pedersen, 2005, Over-the-counter markets, *Econometrica* 73(6), 1815–1847.

Easley, David, and Maureen O'Hara, 1987, Price, trade size, and information in securities markets, *Journal of Financial Economics* 19, 69-90.

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate bond market transaction costs and transparency. *Journal of Finance* 62, 1421–1451.

Feldhütter, Peter, 2012, The same bond at different prices: identifying search frictions and selling pressures, *Review of Financial Studies* 25(4), 1155–1206.

Friewald, Nils, Rainer Jankowitsch, and Marti G. Subrahmanyam, 2012, Illiquidity or credit deterioration: A study of liquidity in the US corporate bond market during financial crises, *Journal of Financial Economics* 105, 18-36.

Garman, Mark B., 1976, Market microstructure, Journal of Financial Economics 3, 257-275.

Gefang, Deborah, Gary Koop, and Simon M. Potter, 2011, Understanding liquidity and credit risks in the financial crisis, *Journal of Empirical Finance* 18, 903-914.

Geske, Robert, 1979, The valuation of compound options, Journal of Financial Economics 7, 63-81.

Geske, Robert, and H. E. Johnson, 1984, The American put option valued analytically, *The Journal of Finance* 39, 1511-1524.

Glosten, Lawrence R., and Paul R. Milgrom, 1985, Bid-ask and transaction prices in a special market with heterogeneously informed traders, Journal of Financial Economics 14, 71-100.

Gromb, Denis, and Dimitri Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, Journal of Financial Economics 66, 361-407.

Grossman, Sanford J., and Merton H. Miller, 1988, Liquidity and Market Structure, *The Journal of Finance* 43, 617-633.

He, Zhiguo, and Wei Xiong, 2012, Rollover risk and credit risk, *The Journal of Finance* 67, 391-430.

He, Zhiguo, and Konstantin Milbradt, 2014, Endogenous liquidity and defaultable bonds, NBERWorking Papers 18408.

Helwege, Jean, Jing-Zhi Huang, and Yuan Wang, 2014, Liquidity effects in corporate bond spreads, *Journal of Banking and Finance* 45, 105-116.

Ho, Thomas, 1981, Optimal dealer pricing under transactions and return uncertainty, *Journal of Financial Economics* 9, 47-73.

Ho, Thomas, and Hans Stoll, 1983, The dynamics of dealer markets under competition, *The Journal of Finance* 38, 1053-1074.

Houweling, Patrick, Albert Mentink , and Ton Vorst, 2005, Comparing possible proxies of corporate bond liquidity, *Journal of Banking and Finance* 29 ,1331-1358.

Huang, Roger D., 2002, The quality of ECN and Nasdaq market maker quotes, *The Journal of Finance* 57, 1285-1319.

Jones, E. Philip, Scott P. Mason, and Eric Rosenfeld, 1984, Contingent claim analysis of corporate capital structures: An empirical investigation, *The Journal of Finance* 39, 611-625.

Kalimipalli , Madhu, and Subhankar Nayak, 2012, Idiosyncratic volatility vs. liquidity: Evidence from the US corporate bond market, *Journal of Financial Intermediation* 21, 217-242.

Kalimipalli, Madhu, Subhankar Nayak, and M. Fabricio Perez, 2013, Dynamic effects of idiosyncratic volatility and liquidity on corporate bond spreads, *Journal of Banking and Finance* 37, 2969-2990.

Kyle, A. S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

Leland, Hayne E., 1994, Corporate debt value, bond covenants, and optimal capital structure, The Journal of Finance 49, 1213-1252.

Leland, Hayne E., and Klaus Bjerre Toft, 1996, Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads 51, 987-1019.

Lin, Hai, Junbo Wang, and Chunchi Wu, 2011, Liquidity risk and expected corporate bond returns, *Journal of Financial Economics* 99, 628-650.

Longstaff, Francis A., and Eduardo Schwarts, 1995, A simple approach to valuing risky fixed and floating rate debt, The Journal of Finance 50, 789-819.

Longstaff, Francis A., Sanjay Mithal, and Eric Neis, 2005, Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market, *The Journal of Finance* 60, 2213-2253.

Lou, Xiaoxia, and Ronnie Sadka, 2010, Liquidity level or liquidity risk? Evidence from the financial crisis, *Financial Analysts Journal* 67, 51-62.

Merton, Robert C., 1973, On the pricing of corporate debt: the risk structure of interest rates, The *Journal of Finance* 29, 449-470.

Mildenstein, Eckart, and Harold Schleef, 1983, The optimal pricing policy of a monopolistic market maker in the equity market, The Journal of Finance 38, 218-231.

O'Hara, Maureen, and George S. Oldfield, 1986, The microeconomics of market making, *The Journal of Financial and Quantitative Analysis* 21, 361- 376.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *The Journal of Political Economy* 111, 642.

Roll, Richard, 1984, A Simple implicit measure of the effective bid-ask spread in an efficient market, *The Journal of Finance* 39, 1127-1139.

Shen, Pu, and Ross M. Starr, 2002, Market makers' supply and pricing of financial market liquidity, Economics Letters 76, 53-58.

Stoll, Hans R., 1978, The supply of dealer services in securities markets, *Journal of Finance* 33, 1133-1151.

Tsuji, Chikashi, 2005, The credit-spread puzzle, *Journal of International Money and Finance* 24, 1073-1089.

Weill, Pierre-Olivier, 2007, Leaning against the wind, *The Review of Economic Studies* 74, 13-29.

Zheng, Harry, 2006, Interaction of credit, and liquidity risks: Modelling and valuation, *Journal of Banking and Finance* 30, 391-407.

APPENDICES

A: Price impact and bid-ask spread proxies

Amihud: The Amihud measure is from Amihud (2002). I calculate the daily Amihud measure as the average ratio of absolute return to the trade size of consecutive transactions during a day:

$$Amihud_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \frac{\left| \frac{P_{i,j} - P_{i,j-1}}{P_{i,j-1}} \right|}{Q_{i,j}}$$

Where $N_{i,t}$ is the number of trades of bond i on day t, $P_{i,j}$ and $P_{i,j-1}$ are the prices for two consecutive trades (j - 1th and jth), for bond i on day t. $Q_{i,j}$ is the size of the jth trade for bond i. At least two transactions are required on a given day to calculate the measure. A larger Amihud measure indicates higher price impact in response to a given volume of trading and reflects higher illiquidity.

Hong and Warga (HW): Based on Hong and Warga (2000) and Chacravarty and Sarkar (2003) measure which uses the difference between the average customer buy and the average customer sell price on each day to quantify transaction costs, I calculate the $Relative\_HW$ and $Absolute\_HW$ measure in the following way:

$$Relative\_HW = \frac{\overline{P_t^{buy}} - \overline{P_t^{sell}}}{0.5 \times (\overline{P_t^{buy}} + \overline{P_t^{sell}})}$$

$$HW = \overline{P_t^{buy}} - \overline{P_t^{sell}}$$

Where $\overline{P_t^{buy}}$ is the average price of all customer buys on day t and $\overline{P_t^{sell}}$ is the average price of all customer sells on day t.

Roundtrip cost (RTC): I measure roundtrip cost in the spirit of Feldhütter (2012). Feldhutter (2012) defines bond trades to be part of an IRT if two or three trades for a given volume occur within fifteen minutes. Such trades are likely part of a pre-matched arrangement in which a dealer has matched a buyer and a seller. Because the buy/sell indicator is not available in the TRACE data for the majority of his study period, he assumes the highest price to be an investor buying from a dealer, the lowest price to be an investor selling to a dealer and the investor roundtrip cost to be the highest minus the lowest price. I modify this measure using buy/sell indicators in the following way: First, I Identify multiple transactions for the same bond on the same day and same volume. Based on this definition 1,897,735 IRTs exist in my sample. 5,518,173, transactions out of 7,988,736 are part of an IRT that form around 69% of total observations. These transaction groups are either S/B: include at least a customer buy and a customer sell transaction, D/B: Include only customer buy and interdealer transactions, S/D: include only customer sell and interdealer transactions, B: Include only customer buy transactions, S: Include only customer sell transactions, D: Include only interdealer transactions. Next I calculate roundtrip cost using the first three types In the following way:

$$RTC = \begin{cases} \overline{p_t^{buy}} - \overline{p_t^{sell}} & \textit{If transaction group is } S/B \\ \overline{p_t^{buy}} - \overline{p_t^{dealer}} & \textit{If transaction group is } D/B \\ \overline{p_t^{dealer}} - \overline{p_t^{sell}} & \textit{If transaction group is } S/D \end{cases}$$

Where $\overline{P_t^{buy}}$ is the mean customer buy price (Ask) and bid $\overline{P_t^{sell}}$is the mean customer sell price and $\overline{P_t^{Dealer}}$ is the mean interdealer price. Finally the daily roundtrip cost for each bond is calculated as the average of all roundtrip costs for that bond during that day.

Riskless principal trades markup (RPT)

Riskless principal trades (RPTs) are offsetting transactions that generate a riskless profit (markup) for the dealer. For example, suppose that a broker-dealer buys a bond at the best available quoted price of 100 on behalf of a client and then sells it to the client at 101, a markup of 1. In these transactions, the broker-dealer typically trades with another dealer first (who provided the quote), and then trades with the client. Harris (2015) studies RPTs as a form of trade throughs when the broker fails to obtain the best available prices for their customers.

We identify RPTs in a similar way to Harris (2015) and Zitzowitz (2010). First, we identify potential RPTs as pairs of sequentially adjacent trades of the same size for which one trade is a customer trade. To find these trades in TRACE data, we need to identify all sequences of two or more trades of equal size. Next for each sequence, we identify potential RPTs if one trade of two adjacent trades within a size run is a dealer trade with a customer, or if both trades in an adjacent pair are customer trades and the dealer both buys and sells. We identify the first such pair as a potential RPT, and then continue searching the size run for any additional pairs that do not involve trades already defined as being a part of a potential RPT. Harris (2015) calls the potential RPTs with both trades in the pair being customer trades as “Crossing RPTs” and potential RPTs with one of the trades being interdealer trade as “Normal RPTs”. Finally, we identify RPTs as those potential RPTs for which the time between the two trades in the pair is one minute or less.

The difference between the two trade prices in a RPT pair is the markup. For crossing RPT trade pairs involving dealer trades with a customer buy and a customer sell, we identify the markup as the difference between the dealer’s sales price to the buyer and the purchase price from the seller. For normal RPT pairs involving an interdealer trade and a sale to a customer, the markup is the customers purchase price minus the interdealer trade price, and vice versa for normal pars involving a dealer purchase from a customer.

To better understand this new measure and to test how it behaves in our data compared to Harris (2015), we replicate some of the analyses in Harris (2015). Panel A of Table 15 reports bond trades classified by position in size-run episodes. For our entire TRACE sample (from July 2002 to September 2014), 69.07% of all trades are in a size-run, 58.19% are in a size run that includes at least one potential RPT pair, and 25.17% are in a potential RPT pair. The normal RPTs involving an interdealer trade are around 12 times more common than the crossing RPTs (1.93%) that involve two offsetting customer trades. The sample includes 2,010,910 trades in 1,005,455 potential RPT pairs. Panel B of Table 15 shows all potential RPT pairs among all bond trades in our sample classified by time between trades in the pair. The reported times of trade (recorded to the second) are exactly the same for 34.83% of the potential RPT pairs, and they are separated by one second or less for 38.34% of these pairs. It is very likely that the same dealers arrange these trades simultaneously. For 61.54% of all potential RPT pairs, the reported time between the trades is 1 minute or less. These trades represent around 15.5% of all trades. All the above rates are higher in Harris (2015) paper. This contrast may suggest that trading in the bond market is becoming more electronic.

Table 16 reports all potential RPT pairs with time between trades of one minute or less among all bond trades in our sample, classified by RPT markup. The markup is zero for 9% of the RPT pairs with trade reports within one minute of each other. The fraction of trades reported with zero markup declines with the length of interval between the two trades (In contrast Harris (2015) who finds 45.4% of RPT pairs with trade reports within one minute of each other have zero markup). To some extent the decline in zero- markup trades with time between trades also may indicate that some trade pairs with non-zero markups are not RPTs since the longer the interval between any two non-RPT trades, the greater the probability that they will be arranged at different prices simply due to price volatility or because different dealers arrange he two trades. Among the potential RPTs 0.6% (3,718) have negative markups. The negative markups are unlikely to be RPTs. Note that the number of trades reported with negative markups rises with the length of the interval between the two trades. Price volatility would explain this results if these trades were not RPTs. Following Harris (2015), we keep the negative-markup RPTs in the sample to ensure that results about mean markup are not upward biased (under the assumption that the distribution of computed markups from the non-RPTs in the set of potential RPTs is symmetric about zero). If indeed, the positive non-RPTs are 0.6% of all trades in the set of potential RPTs, the other positive mark-up RPTs represent 88% of the potential RPTs.

We also eliminated three types of potential RPTs (with time between trades of 1 minute or less) from my analysis: 1. RPTs that their markups exceed -5% and 5% of the average of the two trade prices for because many of them may be the result of trading or report errors that apparently were not corrected. 2. All zero-difference price pairs, because they most likely are agency trades. 3. Potential RPTs with Markups between -10 and 10 bp, because many of these markups may be a natural consequence of net trade pricing without commissions. The remaining sample has 463,706 potential RPT pairs. The average markup in the remaining sample is 77.6 bp of price for all trades and 72.6 bp for trades reported within 1 second of each other. The markup rises after 0 second. It is 71 bp for 0 second. It jumps to 88.5 bp at 1 second and remains above 90 bp for 2, 3 and 4 seconds time interval. It appears that RPT trades that are arranged automatically have smaller markups. The larger markups at the longer intervals may be due to price volatility affecting any non-RPTs in this sample, or to dealers pricing trades that may be costlier for them to arrange, and thus take longer. The total value of these markups is around $141M. The markups occur on customer trades with a reported aggregate market trade volume of $25B. Results in Table 17 show that retail-size trades ($100,000 or less in par value) are a greater fraction of the potential RPTs (92.4%) than they are of all trades (78.56% from Table 2) and IRT trades (80.99%). Mean markups for these trades also are larger than for institutional-size trades at 78.8 bp versus 63.8 bp. Retail traders probably pay markups more often and at higher values because they are less able to negotiate trades than can institutional buy-side traders. Among institutional-size trades, markups and markup values are highest for smaller trades. These results suggest that automated trade systems might most benefit retail traders and small institutional traders. The aggregate markup values for retail-size and institutional-size customer RPT trades are respectively \$68.73M and \$72.13M.

Table 15: Trade classifications by position in size-run episode and time elapsed

Panel A: Trade Classification	Number	Percentage
All trades	7,988,836	100.00
All trades in a size-run episode	5518173	69.07
All trades in a size-run episode with a RPT pair	4648757	58.19
Trades in a RPT pair	2010910	25.17
Trades in a normal RPT pair	1856732	23.24
Trades in a crossing RPT pair	154178	1.93
Non-RPT trades in a size-run episode with a RPT pair	2637847	33.02
Trades in a size-run episodes without a RPT pair	869416	10.88
Trades not in a size-run episode	2,470,663	30.93
Panel B: Elapsed time between trades in the RPT pair		
All RPT pairs	1005,455	100.00
≤1 minute (potential RPT)	618,731	61.54
≤1 Second (potential electronic RPT)	385,501	38.34
0s	350,204	34.83
1s	35,297	3.51
2s	27,480	2.73
3s	19,404	1.93
4s	14,846	1.48
5s	15,830	1.57
6 to 10s	37,525	3.73
11 to 20s	33,057	3.29
21 to 60s	85,088	8.46
1 to 5 min	66,229	6.59
5+ min	320,495	31.88

Table16: Potential RPT pairs with time between trades of one minute or less. Col% indicates column percentage and R.%

Elapsed time between trades in the RPT pair	All RPT pairs		RPT markup									
			Negative			Zero			Positive		
	N	Percent	N	Col%	R%	N	Col%	R%	N	Col%	R.%
≤1 minute (potential RPT)	618,731	100.0	3,718	100.0	0.6	55,971	100.0	9.0	559,042	100.0	90.4
≤1 Second (potential electronic RPT)	385,501	62.3	1,103	29.7	0.3	32,867	58.7	8.5	351,531	62.9	91.2
0s	350,204	56.6	952	25.6	0.3	29,528	52.8	8.4	319,724	57.2	91.3
1s	35,297	5.7	151	4.1	0.4	3,339	6.0	9.5	31,807	5.7	90.1
2s	27,480	4.4	102	2.7	0.4	1,685	3.0	6.1	25,693	4.6	93.5
3s	19,404	3.1	69	1.9	0.4	1,335	2.4	6.9	18,000	3.2	92.8
4s	14,846	2.4	62	1.7	0.4	1,020	1.8	6.9	13,764	2.5	92.7
5s	15,830	2.6	54	1.5	0.3	990	1.8	6.3	14,786	2.6	93.4
6 to 10s	37,525	6.1	325	8.7	0.9	3,371	6.0	9.0	33,829	6.1	90.2
11 to 20s	33,057	5.3	443	11.9	1.3	4,193	7.5	12.7	28,421	5.1	86.0
21 to 60s	85,088	13.8	1,560	42.0	1.8	10,510	18.8	12.4	73,018	13.1	85.8

Table17: Total markup values for potential RPT pairs.

Elapsed time between trades in the RPT pair	N	Mean RPT markup (bp)	Mean Markup value ($)	Total Markup value ($M)	Total dollar trade volume ($B)
≤1 minute (potential RPT)	463,706	77.6	300	140.85	25
≤1 Second (potential electronic RPT)	290,262	72.6	230	66.48	11
0s	262,849	71.0	220	59.03	9.7
1s	27,413	88.5	270	744	1
2s	23,011	90.3	260	613	0.8
3s	16,046	91.5	250	403	0.6
4s	11,944	91.2	270	327	0.5
5s	11,269	78.3	230	264	0.4
6 to 10s	26,500	78.6	330	872	1.71
11 to 20s	23,648	84.7	610	1437	2.91
21 to 60s	61,026	86.9	570	3519	7.54

B: Tobit regressions for liquidity measures

Table 18: Regressions for liquidity proxies

This table repeats the analysis in Table 4 using Tobit regression model for the liquidity proxies with left-censored distributions including Amihud, RTC, HW,RPT and Zero and OLS regression for Log (#Trades) and Log (Vol.). Aa/AA,…, C are dummy variables equal to one if Moody's rating class for the bond is Aa (Aa or Aa2 or Aa3),…C, and zero otherwise. If the bond is not rated by Moody's, S&P rating is used. Control variables are defined both in Table 2 and the text. *Utility* is a dummy variable equal to one, if the issuer belongs to utility industry group and zero otherwise. *Finance* is a dummy variable equal to one if the issuer is a financial firm and zero otherwise. For Tobit models, z-statistics are calculated using robust standard errors. For OLS regressions, t-statistics are calculated using firm level clustered robust standard errors.

	Price impact	Bid-ask spread			Trading activity		
	Amihud	RTC	HW	RPT	Log(#Trades)	Log(Vol.)	Zero
Rating dummies:							
Aa/AA	-0.06***	-0.06***	-0.17***	0.01	-0.01	0.05	-2.11***
A	-0.03**	-0.01	-0.09***	0.05***	0.01	0.07	-2.74***
Baa/BBB	0.03**	0.08***	0.07***	0.12***	0.02	0.10	-2.55***
Ba/BB	0.10***	0.15***	0.23***	0.18***	0.50***	0.81***	-13.63***
B	0.13***	0.12***	0.17***	0.11***	0.44***	0.75***	-11.70***
Caa/CCC	0.19***	0.08***	0.23***	0.13***	0.88***	1.20***	-20.78***
Ca/CC/C	0.51***	-0.12***	-0.07*	-0.06***	0.31**	0.80***	-7.64***
Bond/firm controls:							
Trade size	0.00***	0.00	0.00	0.00	0.00***	0.00***	0.00***
% Inst. trades	-0.98***	-0.65***	-1.97***	-0.34***	-0.94***	3.45***	22.64***
Maturity	0.02***	0.02***	0.06***	0.02***	-0.01***	-0.01***	0.27***
Coupon	0.03***	0.05***	0.06***	0.02***	-0.10***	-0.14***	2.86***
Age	0.00**	0.00***	0.01***	-0.01***	0.00	-0.03***	-0.12***
Issue size	0.07***	0.05***	-0.09***	0.07***	1.70***	2.44***	-61.36***
Coupon freq.	0.01***	0.01***	0.00	0.01*	-0.13***	-0.22***	2.69***
# Issuer bonds	0.00***	0.00	0.00***	0.00***	0.00	0.00	-0.10***
Utility	0.09***	0.09***	0.03	-0.04***	-0.45***	-0.69***	9.39***
Finance	0.06***	0.00	0.04***	-0.01	0.13***	0.17***	-3.29***
Intercept	0.62***	0.51***	1.50***	0.49***	3.80***	0.94***	39.87***
Year fixed effect	Y	Y	Y	Y	Y	Y	Y
# Bonds	3,478	3,379	3,082	2,450	3,478	3,478	3,478
Obs	129,573	120,660	93,977	61,567	129,573	129,573	129,573
Left-censored	2,442	5288	3668	512	0	0	12285

Table 19: Piecewise regressions.

This table repeats the analysis in Table 5 using Tobit regression model for the liquidity proxies with left-censored distributions including Amihud, RTC, HW,RPT and Zero and OLS regression for Log (#Trades) and Log (Vol.). The regression model is in the following form:

$$ILLIQ_{it} = \alpha_1 + \delta_k + \alpha_2 Junk_{it} + \beta_1 Rating_{it} + \beta_2 Junk_{it} \times (Rating_{it} - 11) + \boldsymbol{Controls}_{it} + \varepsilon_{it}$$

Rating is the numerical translation of Moody's rating: 1=Aaa, 21=C. *Junk* is a dummy variable equal to one if the Moody's rating for the bond is between 11=Ba to 19=Caa and equal to zero if the rating for the bond is investment grade. δ_k denotes the year fixed effect. $\boldsymbol{Controls}_{it}$, denotes the matrix of control variables. For Tobit models, z-statistics are calculated using robust standard errors. For OLS regressions, t-statistics are calculated using firm level clustered robust standard errors.

	Price impact	Bid-ask spread			Trading activity		
	Amihud	RTC	HW	RPT	Log(#Trades)	Log(Vol.)	Zero
Rating (β_1)	0.02***	0.01***	0.02***	0.01***	0.02**	0.03***	-0.16
	(23.59)	(10.00)	(10.67)	(8.26)	(2.53)	(3.97)	(-1.01)
Junk (α_2)	-0.03***	0.09***	0.16***	0.09***	0.31***	0.46***	-7.05***
	(-2.83)	(7.43)	(6.77)	(7.52)	(3.71)	(3.78)	(-3.32)
Junk×(Rating-11)(β_2)	-0.00	-0.01***	-0.01*	-0.02***	0.04*	0.02	-0.75
	(-1.10)	(-3.34)	(-1.84)	(-5.84)	(1.73)	(0.56)	(-1.44)
Intercept (α_1)	0.46***	0.45***	1.31***	0.50***	3.72***	0.8***	33.06***
	(27.01)	(28.16)	(39.25)	(26.84)	(29.08)	(4.45)	(10.06)
Controls	Y	Y	Y	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y	Y	Y	Y
# Bonds	3,478	3,379	3,082	2,450	3,478	3,478	3,478
Obs	129,573	120,660	93,977	61,567	129,573	129,573	129,573
Left-censored	2,442	5288	3668	512	0	0	12285

*indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table 20: Regressions for liquidity proxies during three sub-periods

This table repeats the analysis in Table 6 using Tobit regression model for the liquidity proxies with left-censored distributions including Amihud, RTC, HW,RPT and Zero and OLS regression for Log (#Trades) and Log (Vol.).

Pre-crisis is the sample period from Jul. 2002 to Nov. 2007, *crisis* is the period from Dec. 2007 to June 2009, *post-crisis* is the period from July 2009 to Sep.2014. Dependent variables, rating dummies and control variables are similar to Table 4. To save space, the coefficients for control variables are not reported. For Tobit models, z-statistics are calculated using robust standard errors.

	Price impact	Bid-ask spread			Trading activity		
	Amihud	RTC	HW	RPT	Log(#Trades)	Log(Vol.)	Zero
Panel A: Pre-crisis period							
Aa/AA	-0.04***	-0.05**	-0.09***	0.01	0.09	0.19	-3.75***
A	-0.04***	-0.02	-0.07***	0.03**	0.15*	0.28**	-4.63***
Baa/BBB	0.01	0.07***	0.10***	0.09***	0.07	0.23*	-1.31***
Ba/BB	0.13***	0.24***	0.35***	0.26***	0.50***	0.82***	-11.8***
B	0.12***	0.24***	0.37***	0.22***	0.48***	0.84***	-10.8***
Caa/CCC	0.12***	0.25***	0.42***	0.20***	1.12***	1.44***	-22.1***
Ca/CC/C	0.59***	-0.01	0.14***	0.02	0.58***	1.07***	-10.6***
Intercept	0.23***	0.28	0.75***	0.39***	3.31***	0.36*	47.3***
# Bonds	3,041	2,946	2,708	2,042	3,041	3,041	3,041
Obs	80,033	72,639	57,788	29,777	80,033	80,033	80,033
Left-censored	2335	4141	3028	361	0	0	5229
Panel B: Crisis period							
Aa/AA	-0.09**	-0.1***	-0.10	0.01	-0.10	-0.08	2.31*
A	0.07*	0.04	0.21***	0.10***	0.15	0.25	-4.22***
Baa/BBB	0.19***	0.07**	0.49***	0.10***	0.10	0.27	-3.05**
Ba/BB	0.26***	-0.15***	0.37***	0.02	0.34*	0.65**	-11.2***
B	0.30***	-0.13***	-0.21*	0.03	0.14	0.40	-6.96***
Caa/CCC	0.59***	-0.22***	0.04	-0.14***	0.70***	1.40***	-20.6***
Ca/CC/C	0.90***	-0.23***	-0.22	-0.17***	0.37	0.88**	-11.9***
Intercept	0.31***	0.12**	1.07***	0.23***	3.33***	0.08	59.19**
# Bonds	1,134	1,125	1,012	901	1,134	1,134	1,134
Obs	12,772	12,351	9,133	7,221	12,772	12,772	12,772
Left-censored	50	422	192	27	0	0	1383
Panel C: Post-crisis period							
Aa/AA	-0.11	-0.06**	-0.6***	-0.03	0.31	0.65	-8.55***
A	-0.11	-0.02	-0.6***	0.00	0.29	0.64	-8.62***
Baa/BBB	-0.09	0.05	-0.5***	0.06	0.39	0.72	-12.2***
Ba/BB	-0.08	0.01	-0.5***	0.06*	1.04***	1.73***	-26.3***
B	-0.05	-0.07*	-0.6***	-0.06	0.89***	1.53***	-21.4***
Caa/CCC	0.01	-0.09**	-0.7***	0.01	0.86**	1.33**	-21.7***
Ca/CC/C	0.26***	-0.21***	-0.7***	-0.12***	0.55	1.48***	-14.1***
Left-censored	0.59***	0.4***	2.0***	0.36***	3.48***	0.06	49.7***
# Bonds	1,203	1,192	1,068	1,029	1,203	1,203	1,203
Obs	36,768	35,670	27,056	24,569	36,768	36,768	36,768
Left-censored	57	725	448	124	0	0	5673

C: AIC and BIC for Autoregressive Markov switching models

Table 21: AIC and BIC for Autoregressive Markov switching models
Blank spaces demonstrate the models for which EM algorithm do not converge

Panel A: Aggregate market time series

# of regimes		AR(1) 2	AR(1) 3	AR(1) 4	AR(2) 2	AR(2) 3	AR(2) 4
Amihud							
Switching AR coefs	AIC	-526.95	-	-	-523.51	-542.09	-
	BIC	-495.08	-	-	-475.79	-470.51	-
Non-switching AR ceofs	AIC	-520.74	-	-	-519.82	-527.33	-
	BIC	-496.84	-	-	-488.01	-487.56	-
RTC							
Switching AR coefs	AIC	-614.74	-	-	-622.25	-626.67	-
	BIC	-582.87	-	-	-574.53	-555.09	-
Non-switching AR ceofs	AIC	-	-624.53	-632.33	-621.96	-627.05	-630.14
	BIC	-	-592.66	-592.50	-590.15	-587.28	-582.42
HW							
Switching AR coefs	AIC	-339.92	-354.81	-365.63	-346.52	-	-369.81
	BIC	-308.05	-307.00	-301.89	-298.80	-	-274.37
Non-switching AR ceofs	AIC	-331.64	-	-341.43	-349.17	-	-
	BIC	-307.74	-	-301.59	-317.35	-	-
RPT							
Switching AR coefs	AIC	-581.1486	-	-	-618.19	-	-
	BIC	-549.2797	-	-	-570.47	-	-
Non-switching AR ceofs	AIC	-582.9162	-598.2856	-	-615.88	-626.55	-
	BIC	-559.0146	-566.4168	-	-584.07	-586.78	-
#Trades							
Switching AR coefs	AIC	852.44	830.86	827.34	813.04	816.68	815.90
	BIC	884.30	878.67	891.08	860.76	888.26	911.34
Non-switching AR ceofs	AIC	829.26	-	-	810.14	-	-
	BIC	853.16	-	-	841.96	-	-
Volume							
Switching AR coefs	AIC	766.73	748.50	737.19	742.24	728.82	714.61
	BIC	798.60	796.31	800.92	789.96	800.40	810.05
Non-switching AR ceofs	AIC	-	774.08	-	763.04	744.6	-
	BIC	-	805.95	-	794.86	784.37	-
Zero							
Switching AR coefs	AIC	481.23	-	-	480.323	-	-
	BIC	513.09	-	-	528.0438	-	-
Non-switching AR ceofs	AIC	521.15	-	515.28	522.265	-	-
	BIC	545.05	-	555.12	554.078	-	-
% RPT Trades							
Switching AR coefs	AIC	408.44	-	-	393.58	391.34	388.70
	BIC	440.31	-	-	441.3	462.92	484.15
Non-switching AR ceofs	AIC	416.41	-	-	407.89	-	-
	BIC	440.31	-	-	439.71	-	-

Table 21 (continued): AIC and BIC for Autoregressive Markov switching model

Panel A (continued): Aggregate market time series

# of regimes		AR(1)			AR(2)		
		2	3	4	2	3	4
% Inter dealer trades							
Switching AR coefs	AIC	437.24	428.82	-	428.32	420.37	-
	BIC	469.11	476.63	-	476.03	491.96	-
Non-switching AR ceofs	AIC	445.26	438.37	426.37	432.07	429.37	-
	BIC	469.16	470.24	466.21	463.88	469.14	-
% Block volume trades							
Switching AR coefs	AIC	462.36	449.45	-	452.95	443.41	-
	BIC	494.23	497.25	-	500.67	514.99	-
Non-switching AR ceofs	AIC	462.17	-	-	451.83	-	-
	BIC	486.07	-	-	483.64	-	-

Table 21 (continued): AIC and BIC for Autoregressive Markov switching models

Panel B: IG - HY time series

# of regimes		AR(1)			AR(2)		
		2	3	4	2	3	4
Amihud							
Switching AR coefs	AIC	-310.97	-	-	-307.82	-	-
	BIC	-279.11	-	-	-260.10	-	-
Non-switching AR ceofs	AIC	-308.86	-	-	-308.40	-	-
	BIC	-284.96	-	-	-276.59	-	-
RTC							
Switching AR coefs	AIC	-316.81	-325.48	-	-332.95	-	-
	BIC	-284.94	-277.68	-	-285.23	-	-
Non-switching AR ceofs	AIC	-318.76	-	-	-329.44	-335.78	-
	BIC	-294.86	-	-	-297.63	-296.01	-
HW							
Switching AR coefs	AIC	-120.25	-	-	-142.93	-	-
	BIC	-88.39	-	-	-95.211	-	-
Non-switching AR ceofs	AIC	-119.21	-	-	-142.43	-	-
	BIC	-95.31	-	-	-110.62	-	-
RPT							
Switching AR coefs	AIC	-318.88	-	-	-330.30	-	-
	BIC	-287.01	-	-	-282.58	-	-
Non-switching AR ceofs	AIC	-309.85	-	-	-326.73	-330.38	-
	BIC	-285.94	-	-	-294.91	-290.61	-
#Trades							
Switching AR coefs	AIC	993.91	-	-	986.81	-	-
	BIC	1025.78	-	-	1034.53	-	-
Non-switching AR ceofs	AIC	996.98	-	-	986.40	-	-
	BIC	1020.88	-	-	1018.21	-	-
Volume							
Switching AR coefs	AIC	874.10	-	-	852.57	-	-
	BIC	905.97	-	-	900.29	-	-
Non-switching AR ceofs	AIC	877.76	-	-	856.30	852.48	-
	BIC	901.66	-	-	888.11	892.25	-
Zero							
Switching AR coefs	AIC	531.11	513.55	-	508.35	-	-
	BIC	562.98	561.35	-	556.07	-	-
Non-switching AR ceofs	AIC	528.96	528.68	-	527.02	529.06	530.99
	BIC	552.87	560.55	-	558.84	568.82	578.71
% RPT Trades							
Switching AR coefs	AIC	646.31	642.69	-	636.26	628.98	-
	BIC	678.18	690.50	--	683.98	700.57	-
Non-switching AR ceofs	AIC	670.56			645.22		
	B ICIIIC	694.46			677.04		